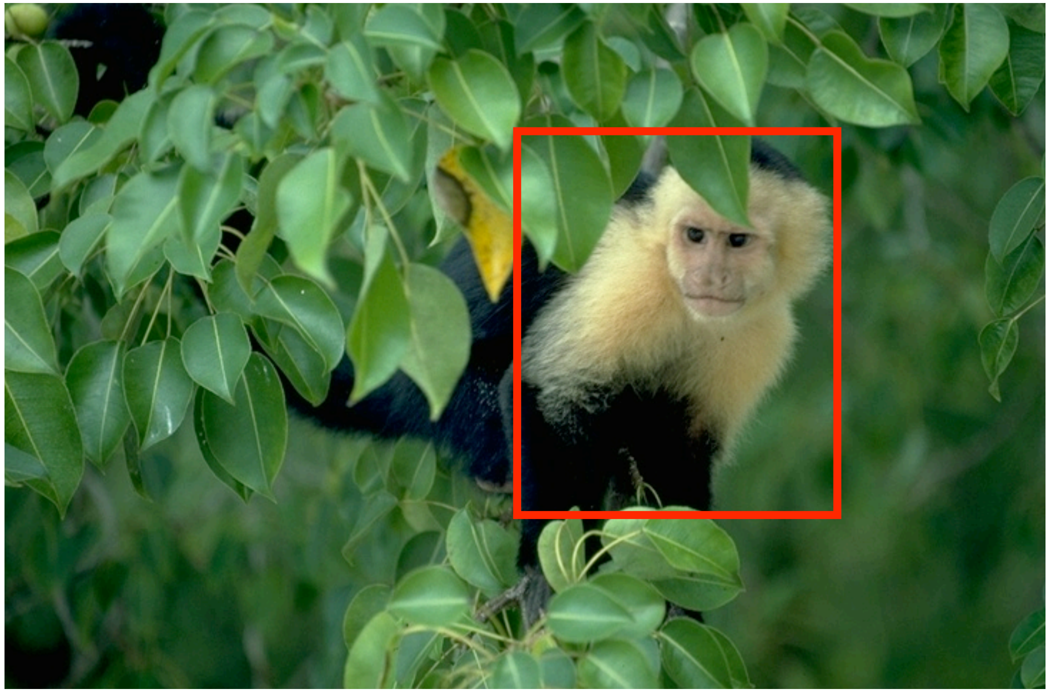
Category-level localization

Cordelia Schmid

Category-level localization

- Localization up to a bounding box
  - Sliding window approach, previous course: Felzenszwalb 2010
  - Today: shape-based descriptor + sliding window



Category-level localization

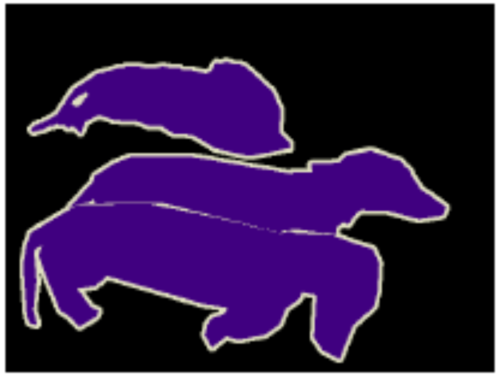
- Localization of object outlines

Learning shape-based models

Localizing the objects with the learnt models

Category-level localization

- Localization of object pixels
  - Pixel-level classification, segmentation


Overview

- *Localization with shape-based descriptors*
- Learning deformable shape models
- Segmentation, pixel-level classification

Shape-based features for localization

- Classes with characteristic shape
  - appearance, local patches are not adapted
  - shape-based descriptors are necessary

[Ferrari, Fevrier, Jurie & Schmid, PAMI'08]

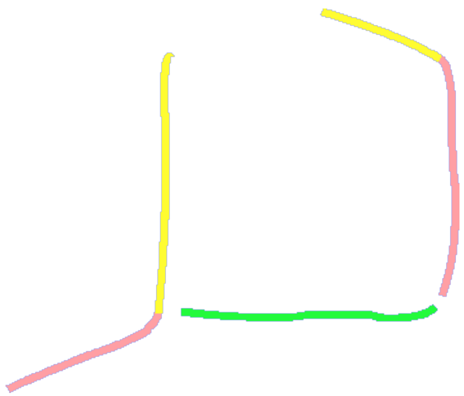
Pairs of adjacent segments (PAS)

Contour segment network

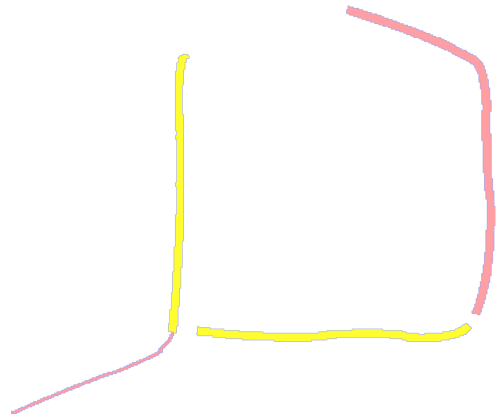
[Ferrari et al. ECCV'06]

1. Edgels extracted with Berkeley boundary detector
2. Edgel-chains partitioned into straight contour segments
3. Segments connected at edgel-chains' endpoints and junctions

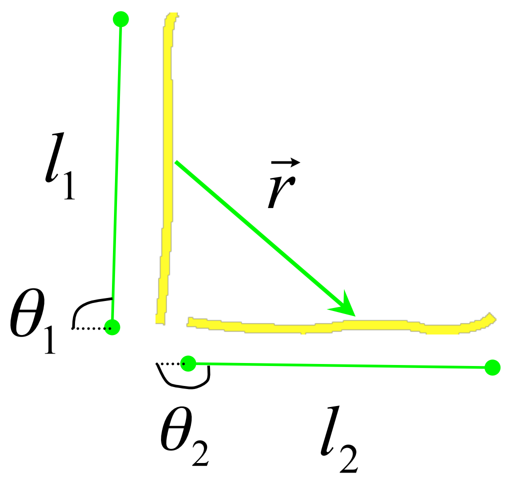
Pairs of adjacent segments (PAS)



Contour segment network



PAS = groups of two connected segments



PAS descriptor:

$$\left(\frac{r_x}{\|\vec{r}\|}, \frac{r_y}{\|\vec{r}\|}, \theta_1, \theta_2, \frac{l_1}{\|\vec{r}\|}, \frac{l_2}{\|\vec{r}\|} \right)$$

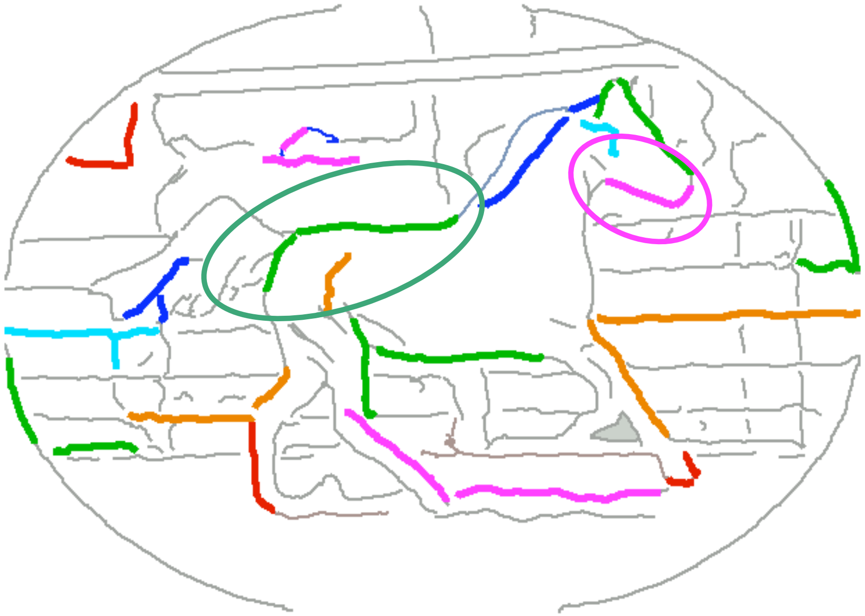
encodes *geometric* properties of the PAS

scale and translation invariant

compact, 5D

Features: pairs of adjacent segments (PAS)

Example PAS



Why PAS ?

+ can cover pure portions of the object boundary

+ intermediate complexity: good repeatability-informativeness trade-off

+ scale-translation invariant

+ connected: natural grouping criterion (need not choose a grouping neighborhood or scale)

PAS codebook

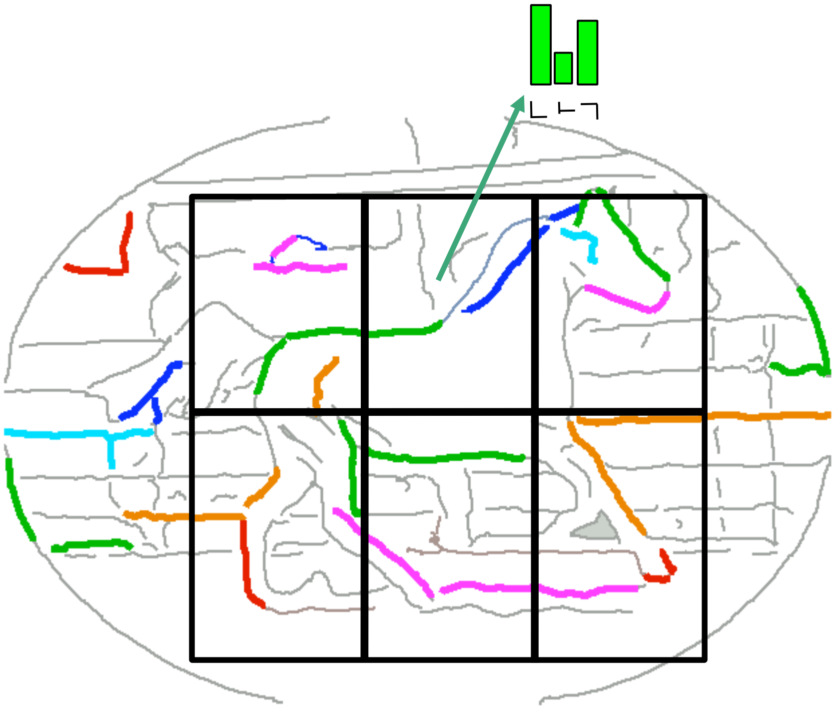
PAS descriptors are clustered into a vocabulary

a few types from 15 indoor images

- Frequently occurring PAS have intuitive, natural shapes
- As we add images, number of PAS types converges to just ~100
- Very similar codebooks come out, regardless of source images

→ general, simple features

Window descriptor



1. Subdivide window into tiles

2. Compute a separate bag of PAS per tile

3. Concatenate these semi-local bags

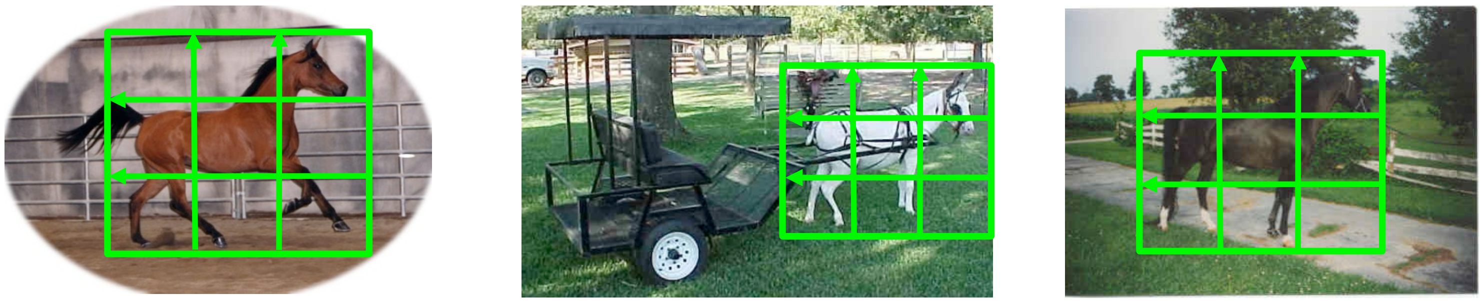
+ distinctive:
  records *which* PAS appear *where*
  weight PAS by average edge strength

+ flexible*:*
  soft-assign PAS to types, coarse tiling

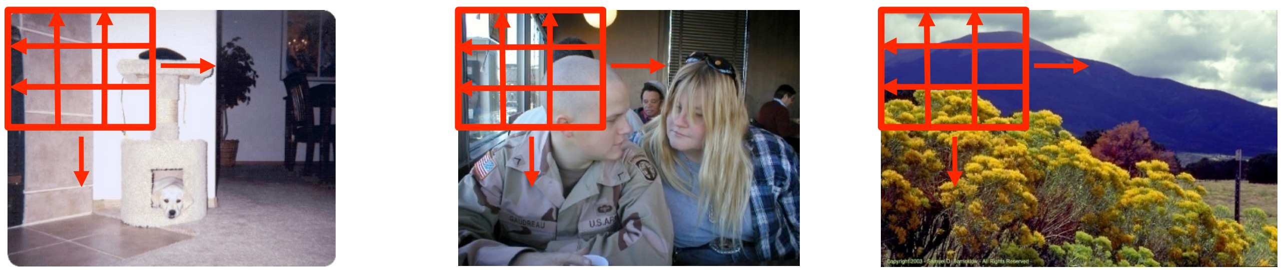
+ fast:
  computation with Integral Histograms

Training

1. Learn mean positive window dimensions $M_w \times M_h$
2. Determine number of tiles T
3. Collect positive example descriptors



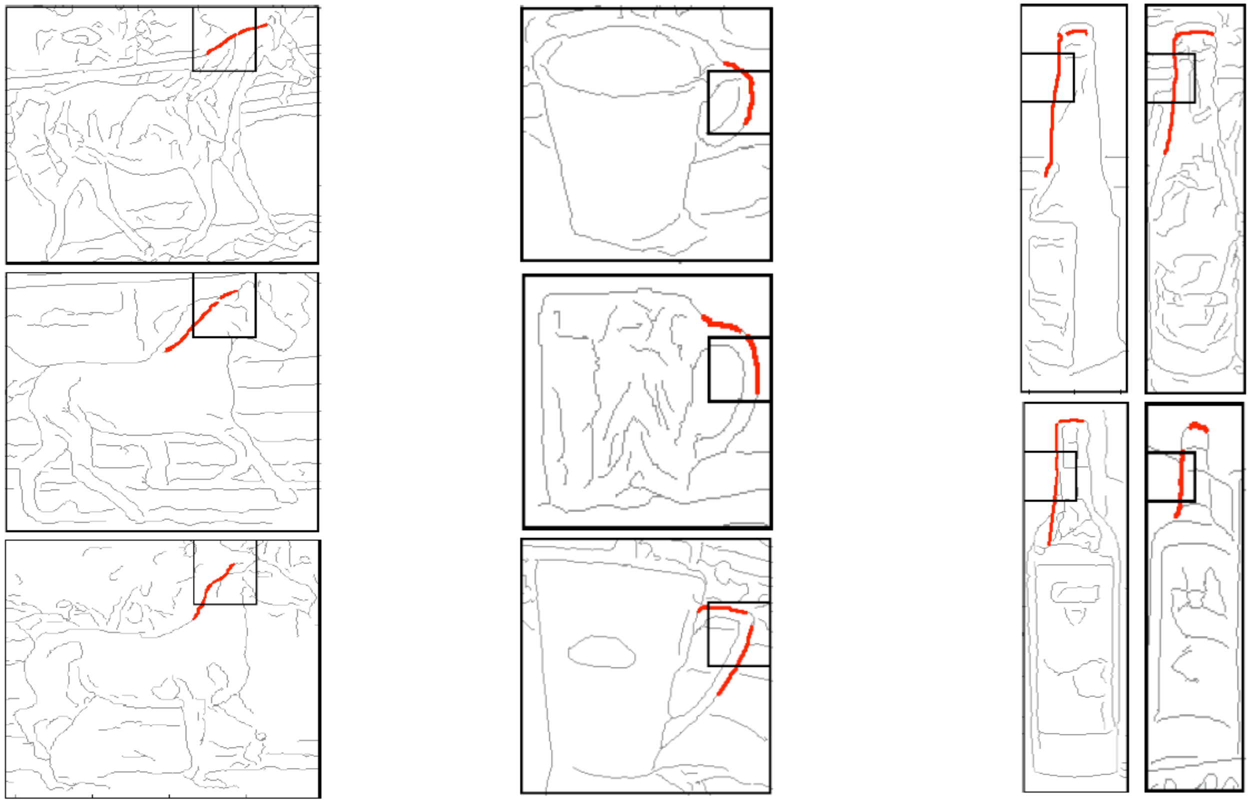
4. Collect negative example descriptors:
   slide $M_w \times M_h$ window over negative training images



Training

5. Train a linear SVM from positive and negative window descriptors

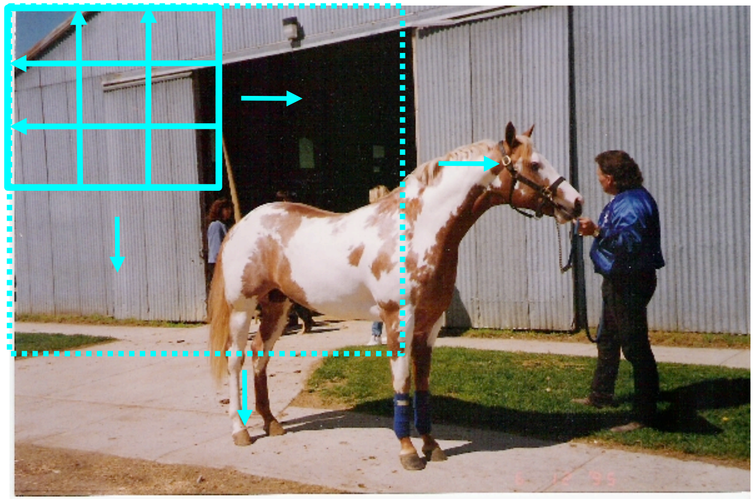
A few of the highest weighed descriptor vector dimensions (= 'PAS + tile')



+ lie on object boundary (= local shape structures common to many training exemplars)

Testing

1. Slide window of aspect ratio M_w / M_h at multiple scales

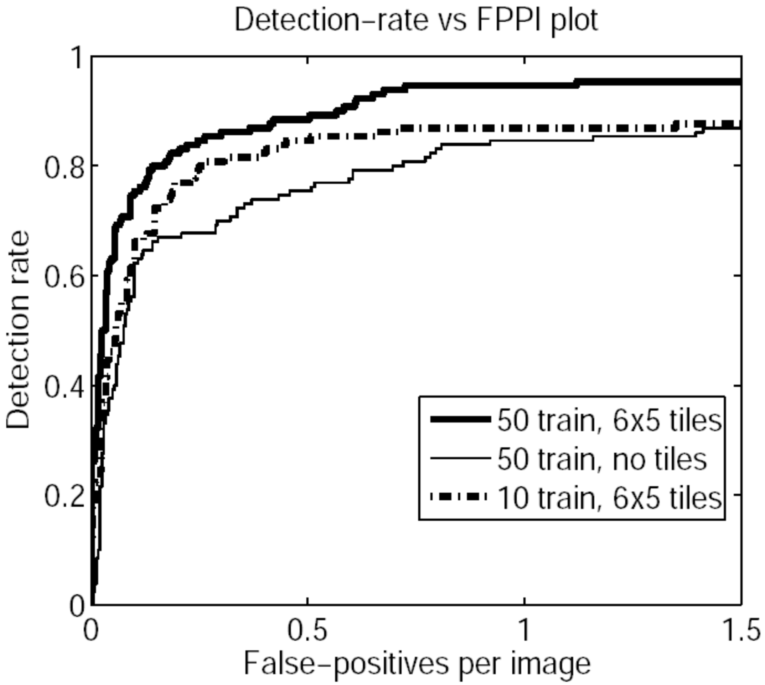


2. SVM classify each window + non-maxima suppression

$\longrightarrow$ detections

Experimental results – INRIA horses

Dataset: 170 positive + 170 negative images (training = 50 pos + 50 neg)
wide range of scales; clutter



(missed and FP)

+ tiling brings a substantial improvement
optimum at T=30 → used for all other experiments

+ works well: 86% det-rate at 0.3 FPPI (50 pos + 50 neg training images)

Experimental results – INRIA horses

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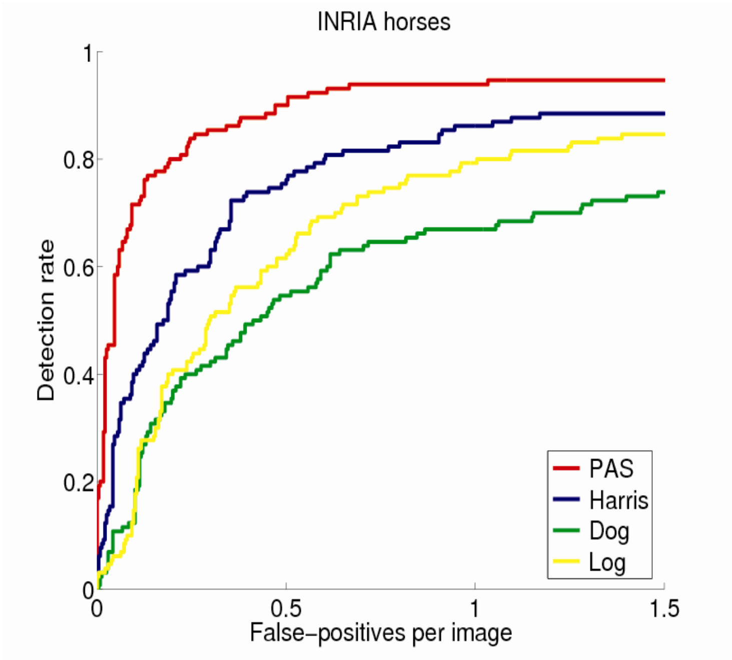
wide range of scales; clutter



+ PAS better than any interest point detector

- all interest point (IP) comparisons with T=10, and 120 feature types (= optimum over INRIA horses, and ETHZ Shape Classes)
- IP codebooks are class-specific

Results – ETH shape classes

Dataset: 255 images, 5 classes; large scale changes, clutter
training = half of positive images for a class
+ same number from the other classes (1/4 from each)
testing = **all** other images

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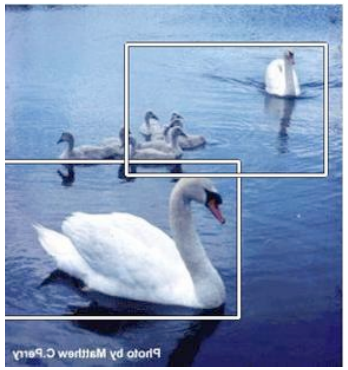


Missed

Results – ETHZ Shape Classes

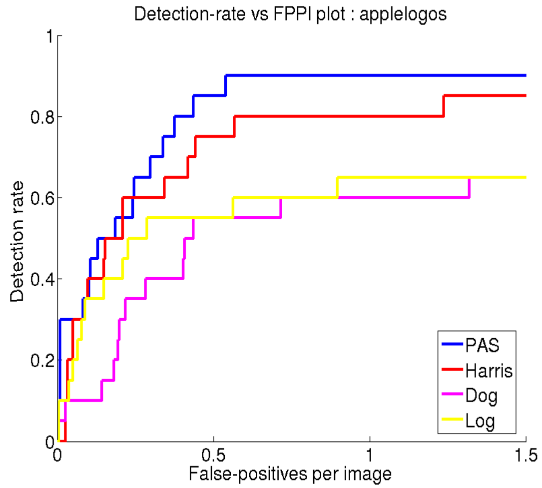
+ mean det-rate at 0.4 FPPI = 79%

+ class specific IP codebooks

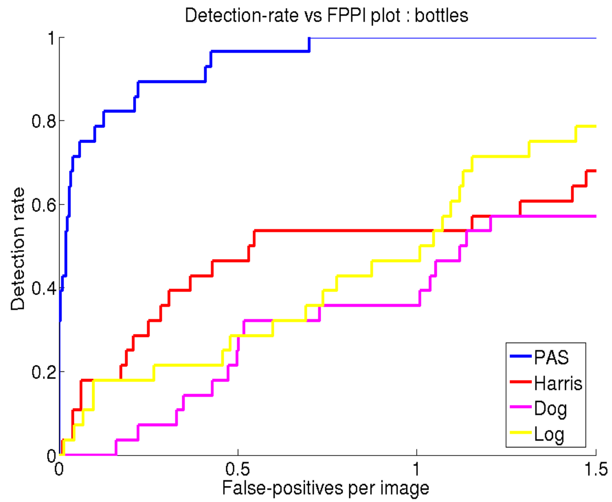
+ PAS >> I.P for
    apple logos, bottles, mugs
  PAS ~= IP for
    giraffes (texture!)
  PAS < IP for
    swan

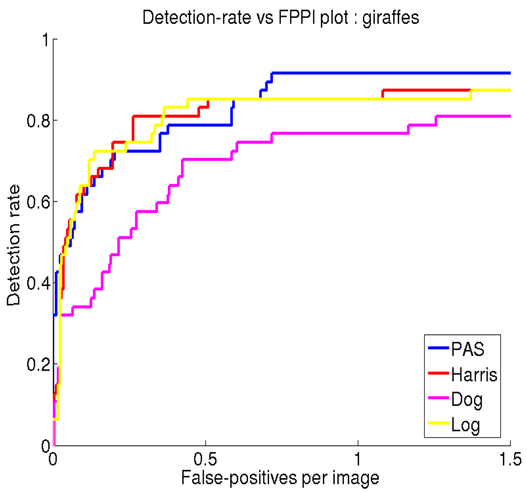
+ overall best IP: Harris-Laplace

Apple logos

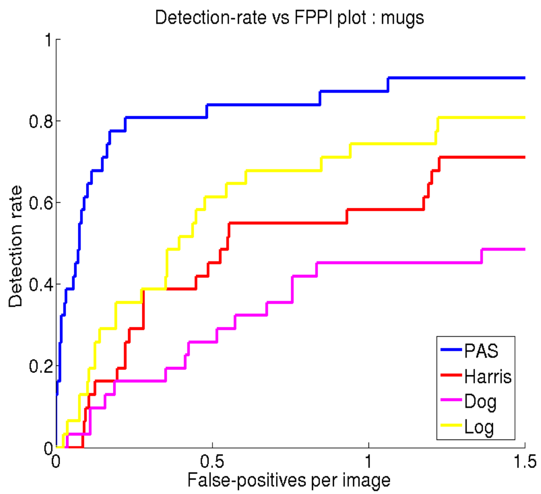


Bottles

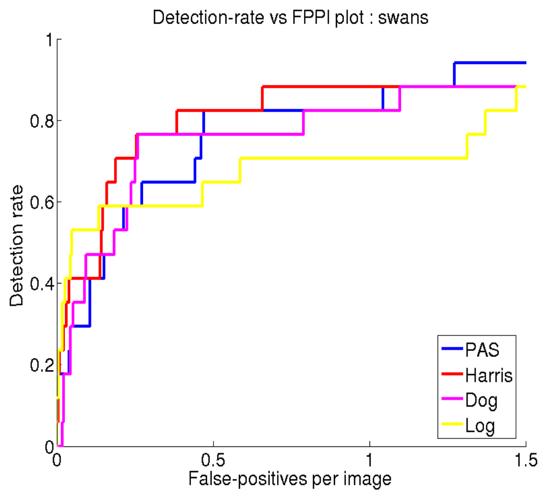




Giraffes



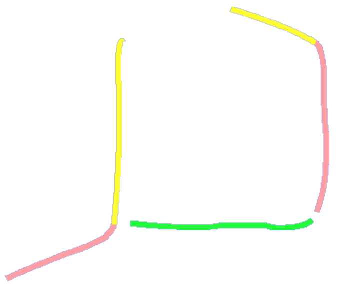
Mugs



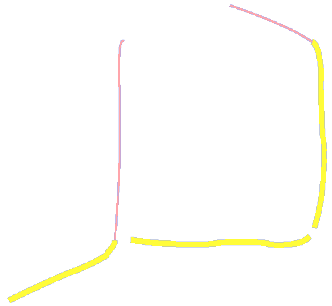
Swans

Generalizing PAS to *k*AS

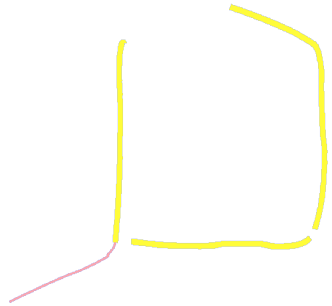
*k*AS: any path of length *k* through the contour segment network



segment network



3AS



4AS

scale+translation invariant descriptor with dimensionality 4*k*-2

k = feature complexity; higher *k* more informative, but less repeatable

overall mean det-rates (%)

	1AS	PAS	3AS	4AS
0.3 FPPI	69	77	64	57
0.4 FPPI	76	82	70	64

PAS do best !

Overview

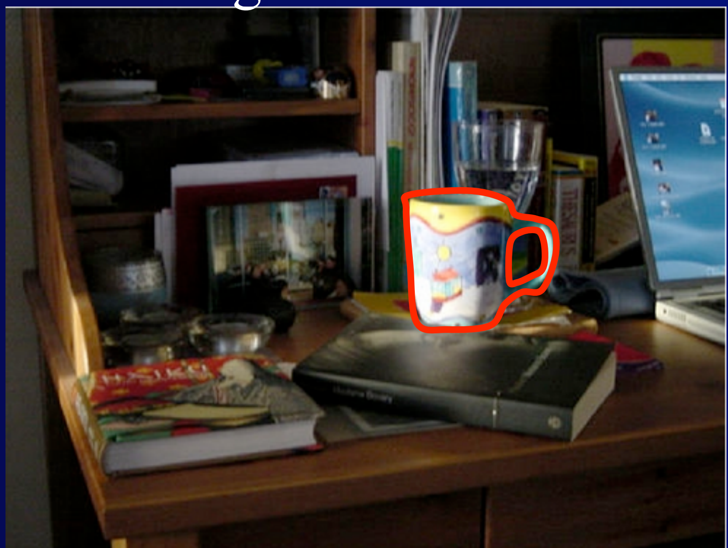
- Localization with shape-based descriptors
- *Learning deformable shape models*
- Segmentation, pixel-level classification

Learning deformable shape models from images

Training data

Goal: localize boundaries of class instances

Test image



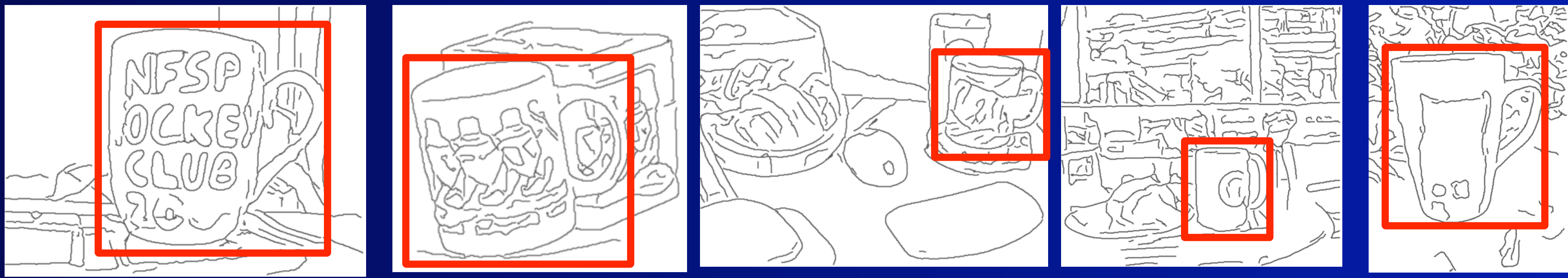
Training: *bounding-boxes*

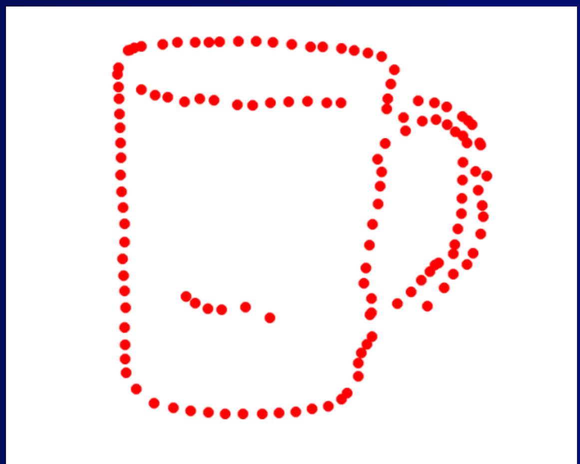
Testing: *object boundaries*

[Ferrari, Jurie, Schmid, IJCV10]

Learn a shape model from training images

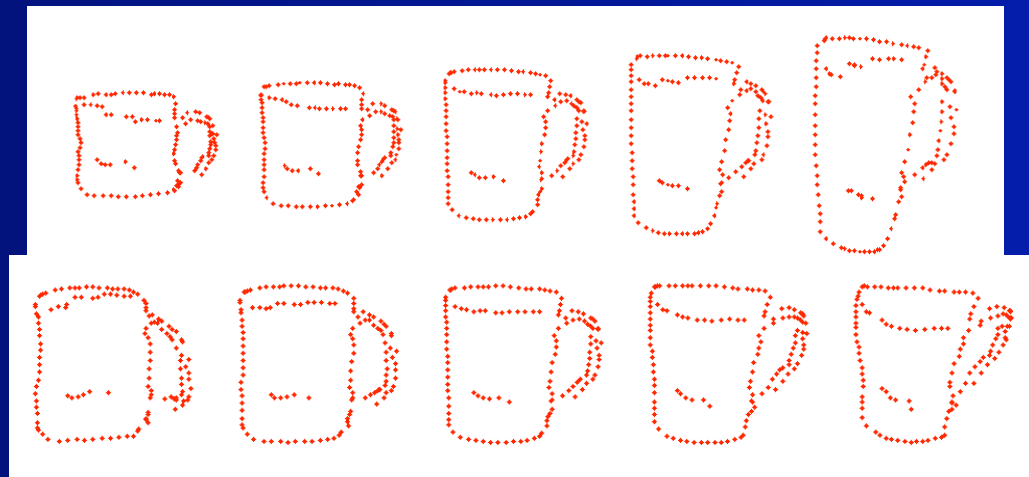
Training data





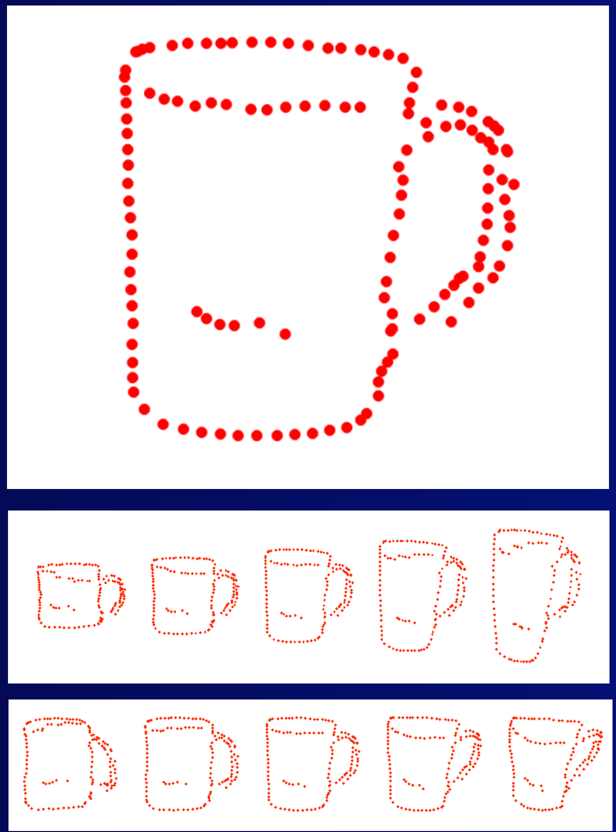
prototype shape

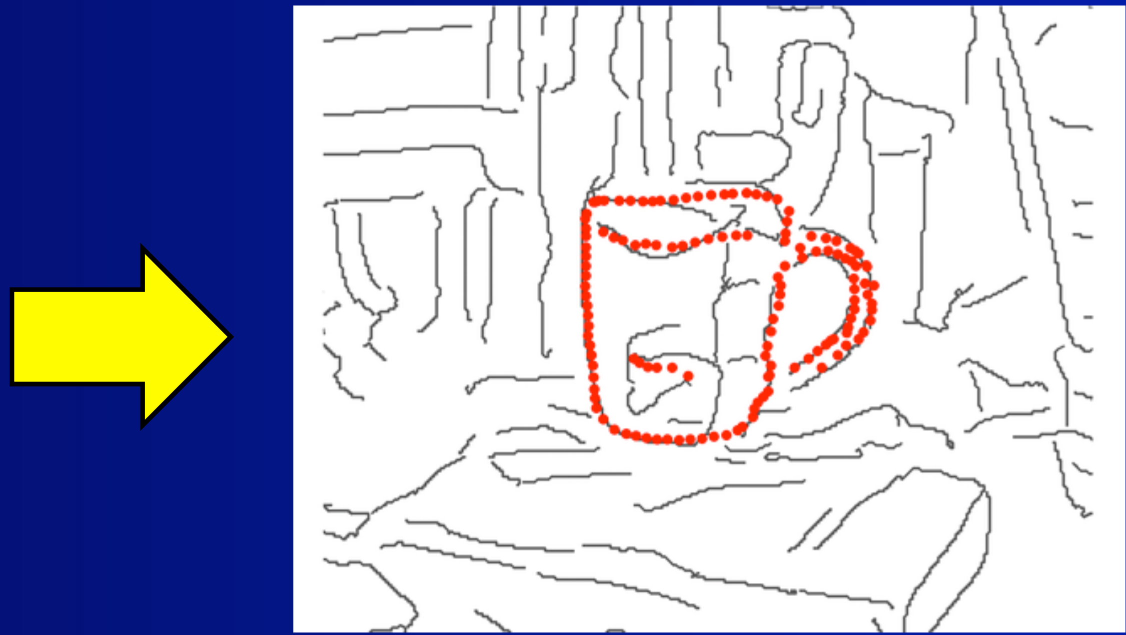
+



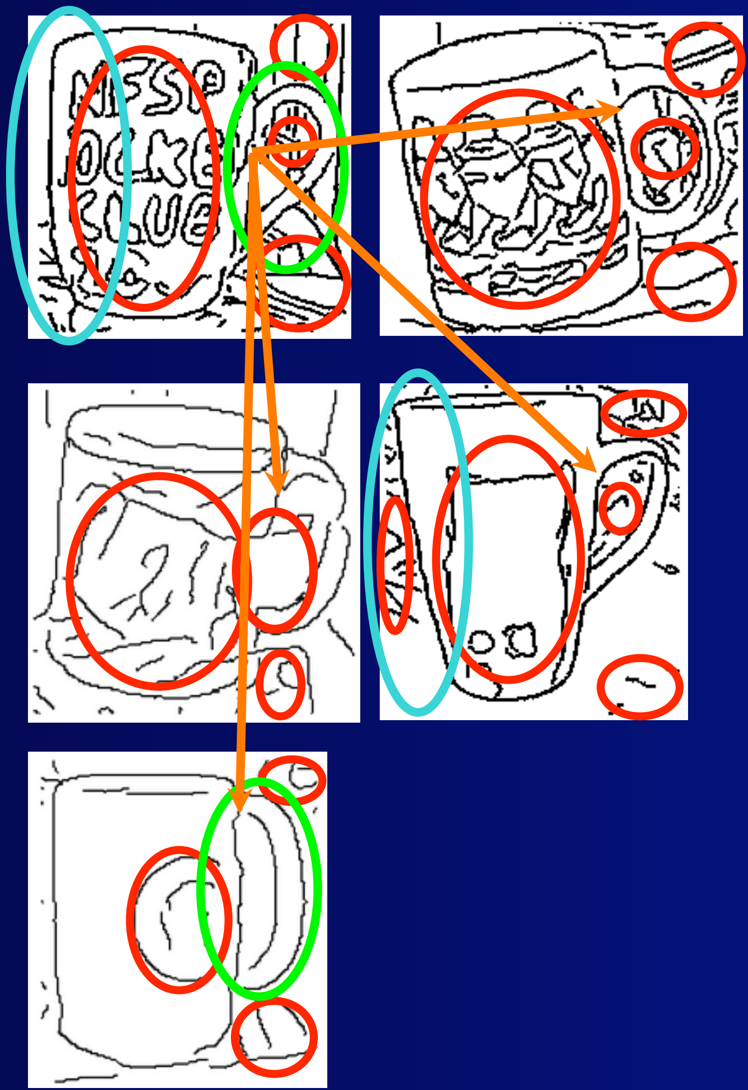
deformation model

Match it to the test image





Challenges for learning



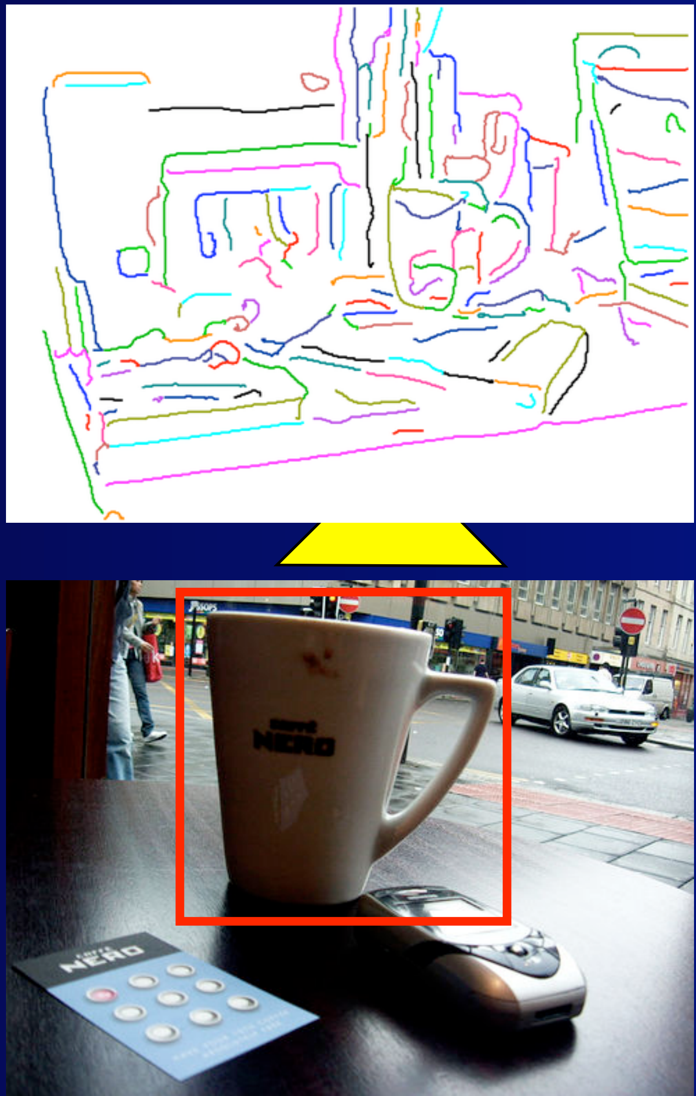
Main issue

which edgels belong
to the class boundaries ?

Complications

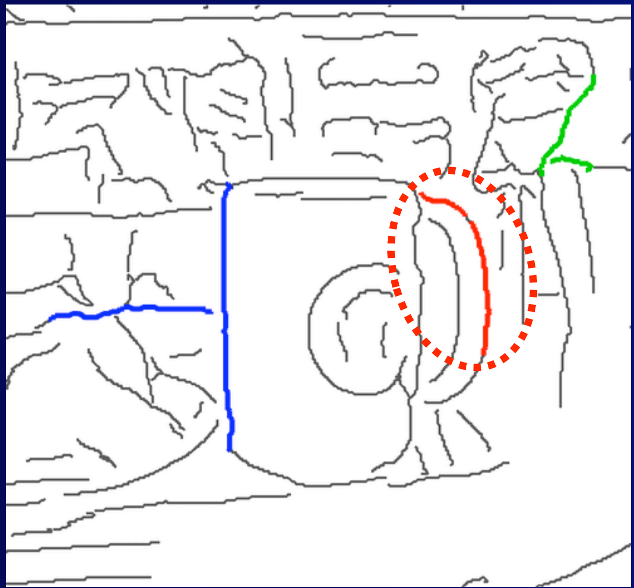
- intra-class variability
- missing edgels
- produce point correspondences
  (learn deformations)

Challenges for detection



- scale changes
- intra-class variability
- clutter
- fragmented and incomplete contours

Local contour features



PAS
Pair of Adjacent Segments

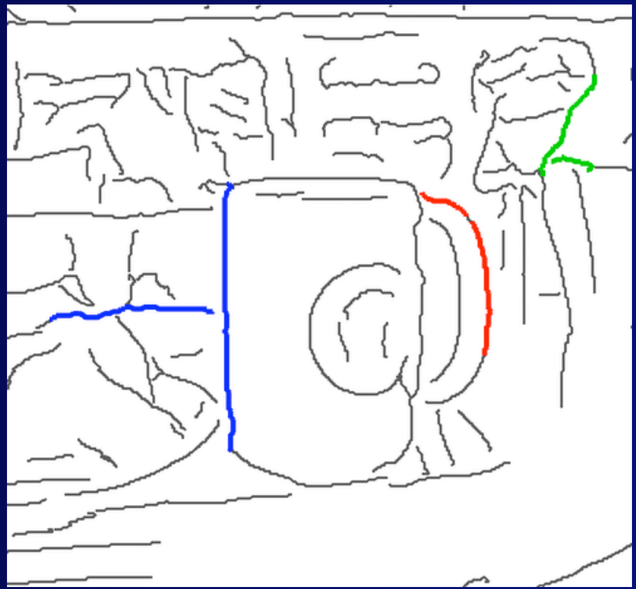
\+ *robust*
connect also across gaps

\+ *clean*
descriptor encodes the two segments *only*

\+ *invariant*
to translation and scale

\+ *intermediate complexity*
good compromise between repeatability and informativity

Local contour features



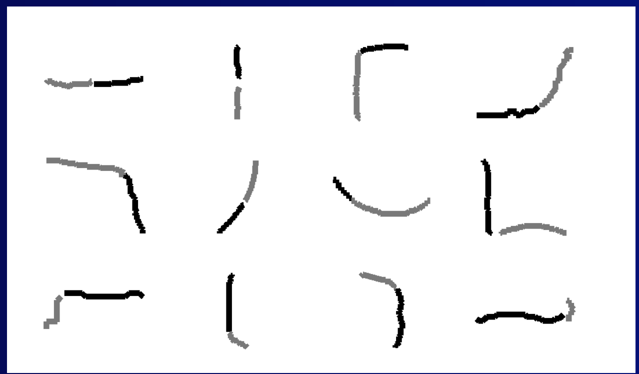
PAS

Pair of Adjacent Segments

two PAS in correspondence

⟶ translation+scale transform

⟶ use in Hough-like schemes

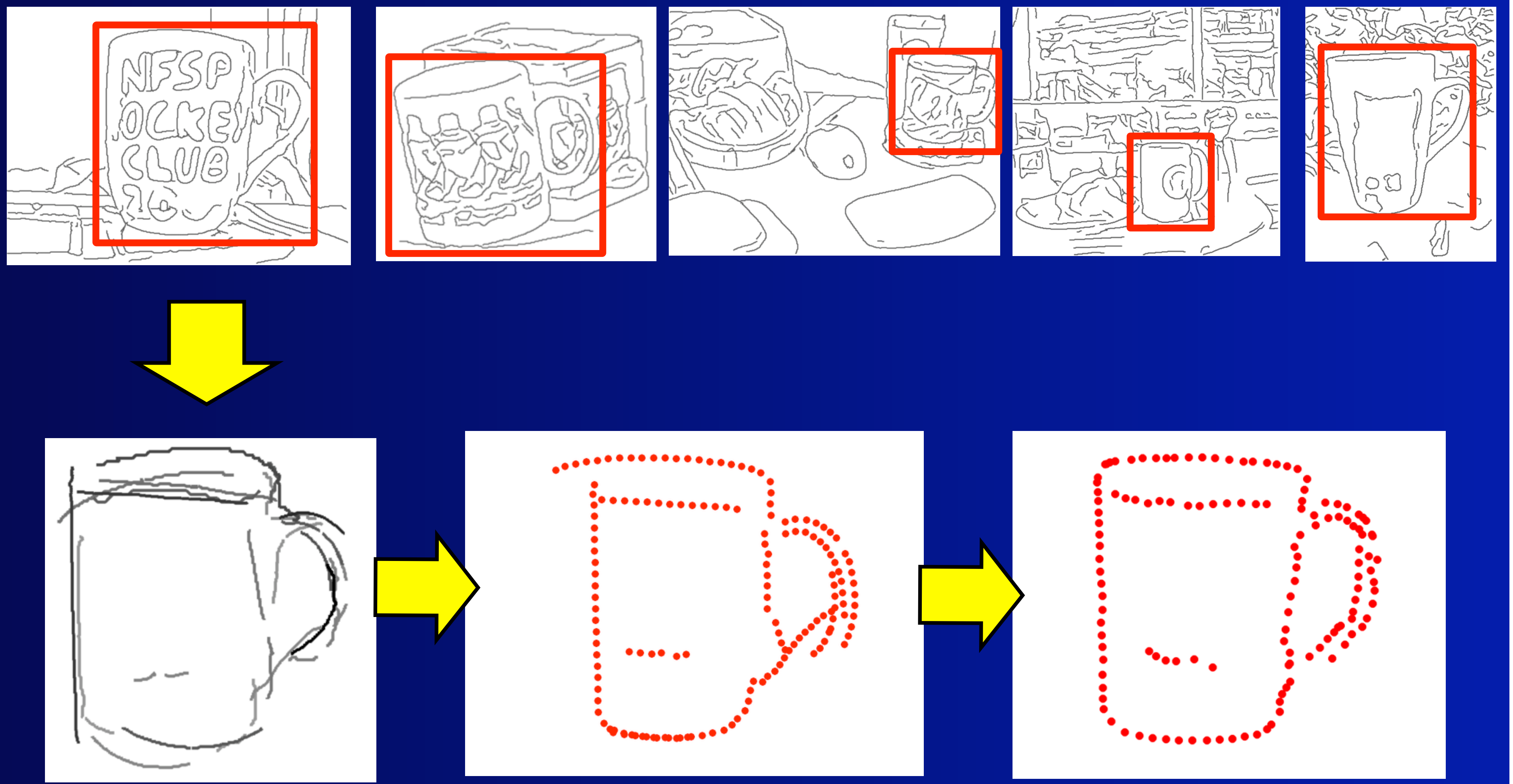


Clustering descriptors

⟶ codebook of *PAS types*

(here from mug bounding boxes)

Learning: overview

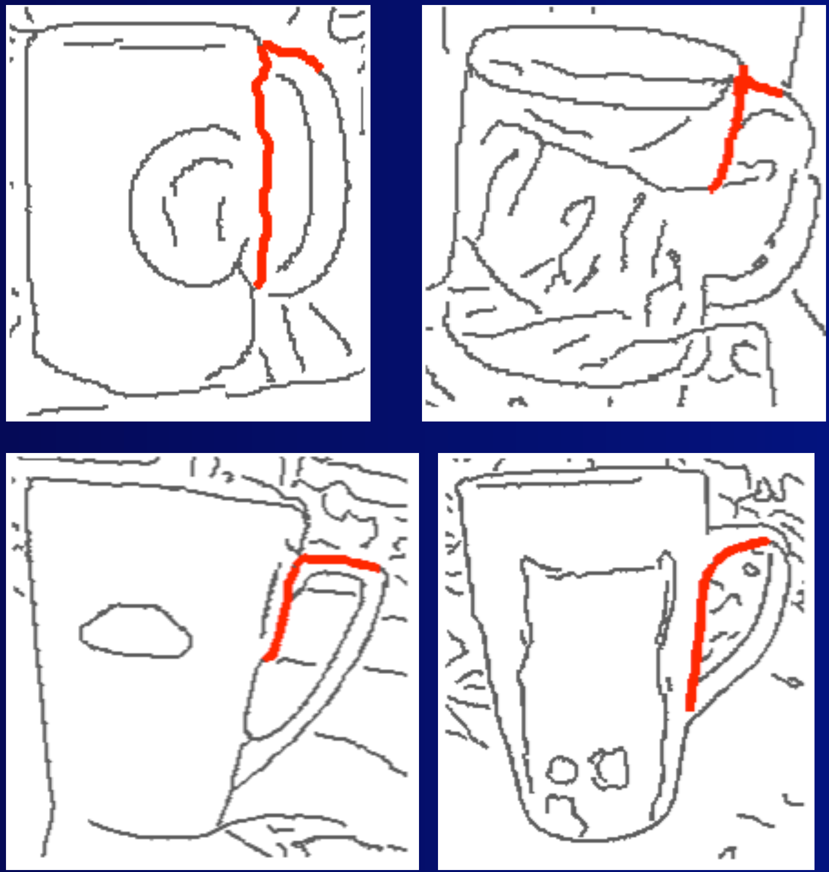


find models parts

assemble an initial shape

refine the shape

Learning: finding model parts

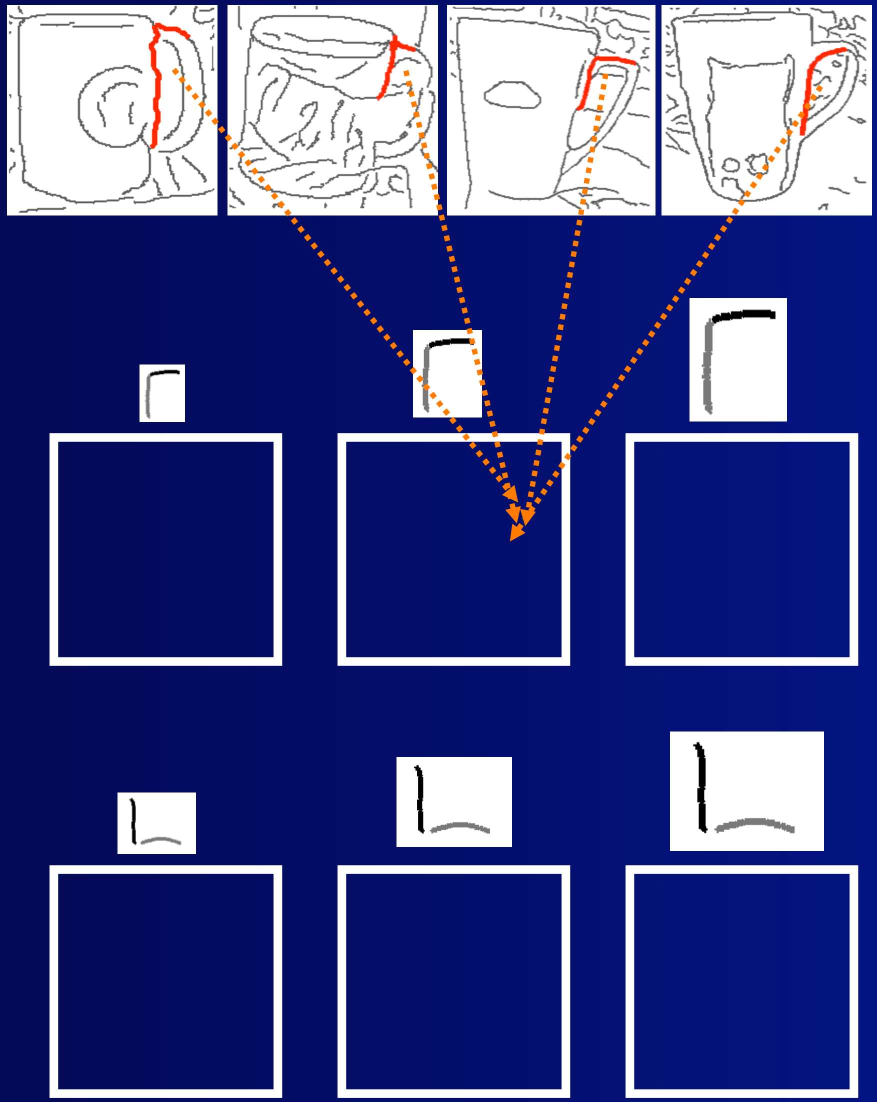


Intuition

PAS on class boundaries reoccur at similar locations/scales/shapes

Background and details specific to individual examples don't

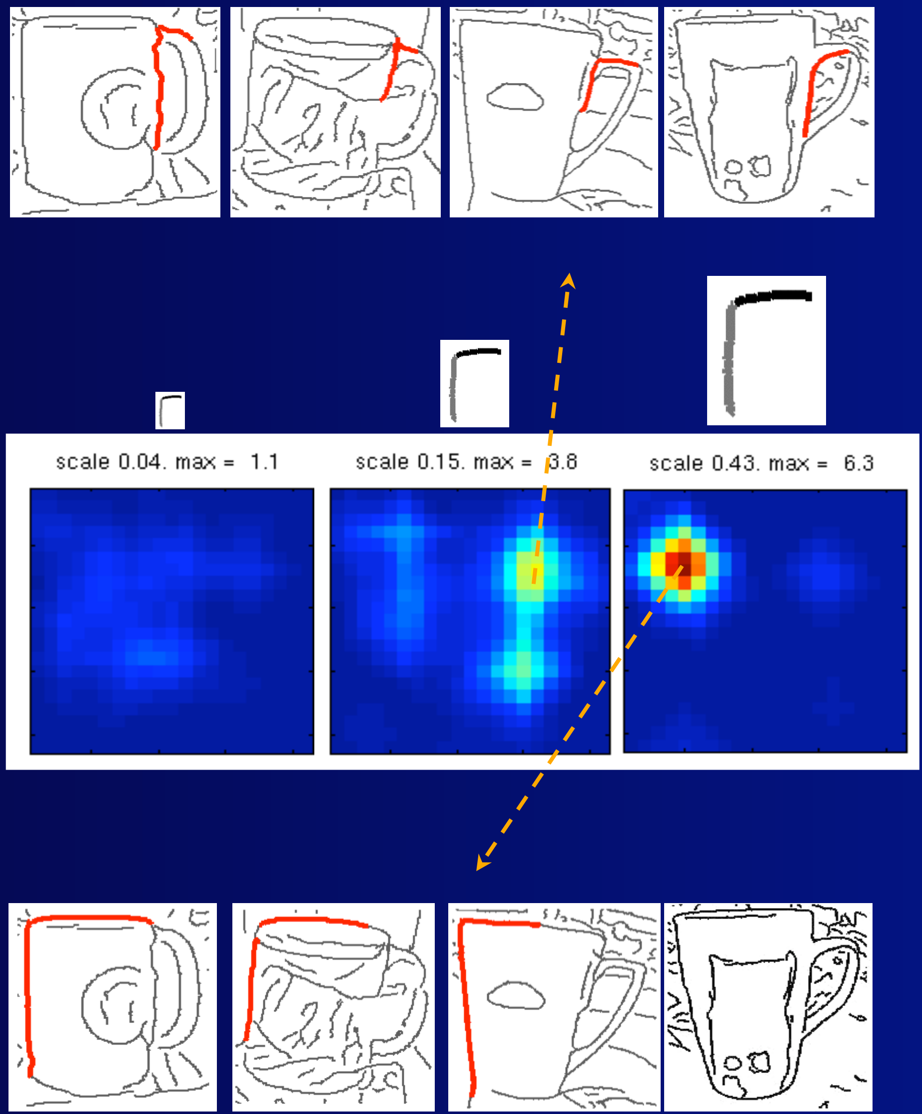
Learning: finding model parts



Algorithm

1. align bounding-boxes up to translation/scale/aspect-ratio
2. create a separate voting space per PAS type
3. soft-assign PAS to types
4. PAS cast 'existence' votes in corresponding spaces

Learning: finding model parts



Algorithm

1. align bounding-boxes up to translation/scale/aspect-ratio
2. create a separate voting space per PAS type
3. soft-assign PAS to types
4. PAS cast ‘existence’ votes in corresponding spaces
5. local maxima ⟶ model parts

Learning: finding model parts

Model parts

- location + size (wrt canonical BB)
- shape (PAS type)
- strength (value of local maximum)

Learning: finding model parts

Why does it work ?

Unlikely unrelated PAS have similar location *and* size *and* shape

⟶ form no peaks !

Important properties

+ see all training data at *once*

⟶ robust

+ linear complexity

⟶ efficient large-scale learning

Learning: assembling an initial shape

best occurrence for each part

Not a shape yet

- multiple strokes
- adjacent parts don’t fit together

Why ?

- parts are learnt *independently*

Let’s try to assemble parts into a proper whole

We want single-stroked, long continuous lines !

Learning: assembling an initial shape

all occurrences in a few training images

Observation

each part has several occurrences

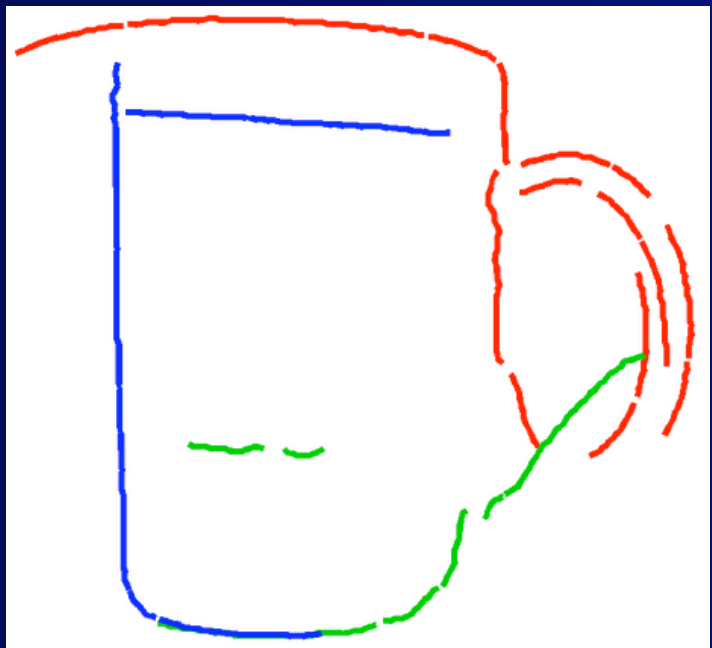
↓

can assemble shape variations by selecting different occurrences

Idea

select occurrences so as to form larger connected aggregates

Learning: assembling an initial shape



Hey, this starts to look like a mug !

+ segments fit well within a block

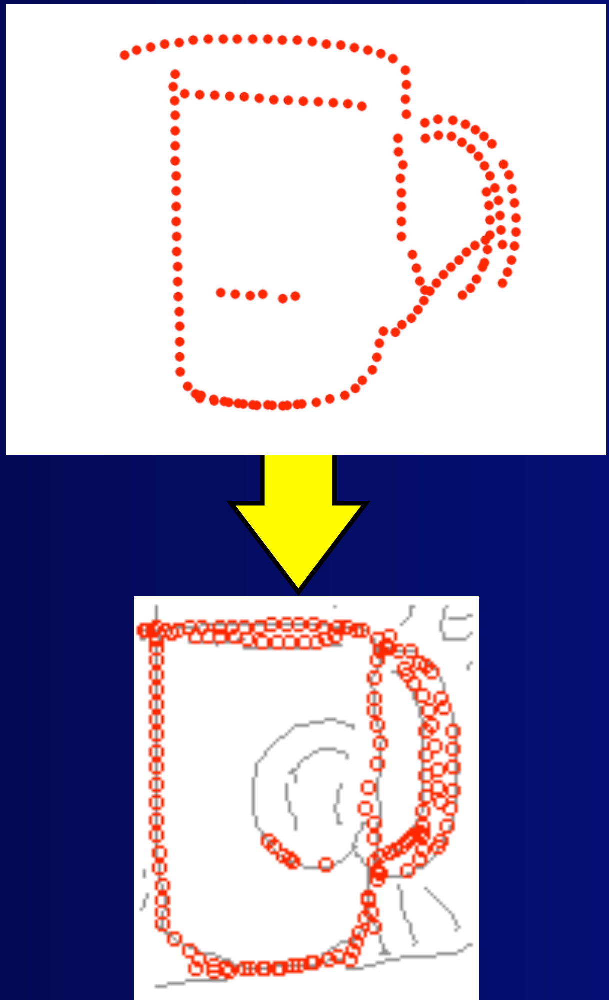
+ most redundant strokes are gone

Can we do better ?

- discontinuities between blocks ?

- generic-looking ?

Learning: shape refinement



Idea

treat shape as deformable point set

and *match it back* onto training images

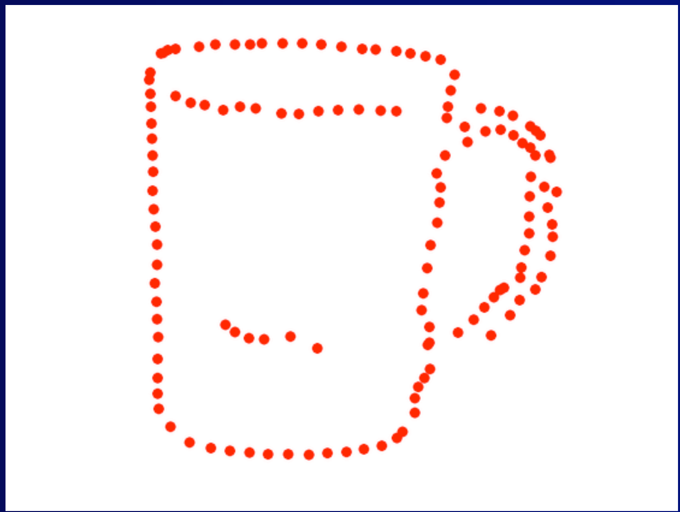
How ?

- robust non-rigid point matcher: TPS-RPM
  (thin plat spline – robust point matching)
- strong initialization:
  align model shape BB over training BB

  ⟶ likely to succeed

Chui and Rangarajan, *A new point matching algorithm for non-rigid registration*, CVIU 2003

Learning: shape refinement



Shape refinement algorithm

1. Match current model shape back to every training image

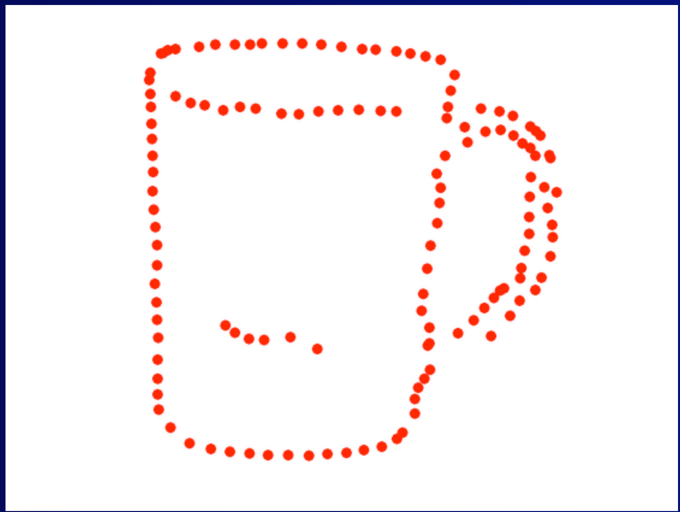
   backmatched shapes are in full point-to-point correspondence !

2. set model to mean shape

3. remove redundant points

4. if changed ⟶ iterate to 1

Learning: shape refinement



Final model shape

+ clean (almost only class boundaries)

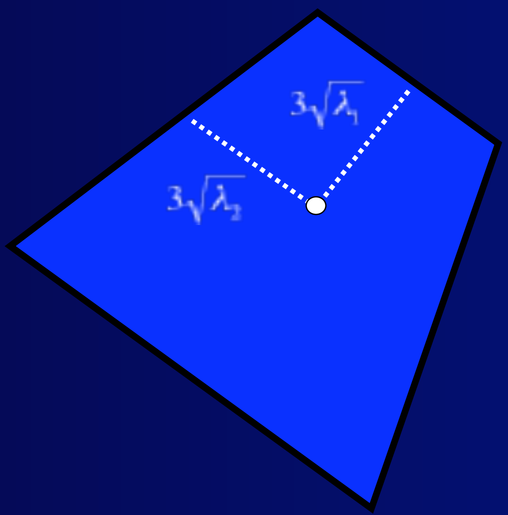
+ smooth, connected lines

+ generic-looking

+ fine-scale structures recovered
  (handle arcs)

+ accurate point correspondences
  spanning training images

Learning: shape deformations



• = mean shape

From backmatching
intra-class variation examples,
in complete correspondence

↓

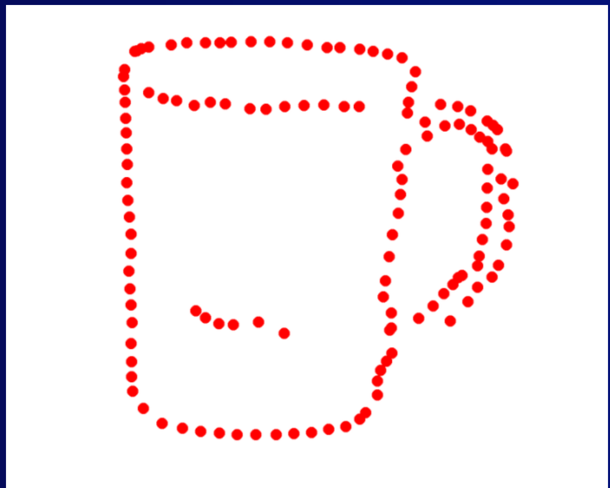
Apply Cootes' technique
1. shapes = vectors in 2p-D space
2. apply PCA

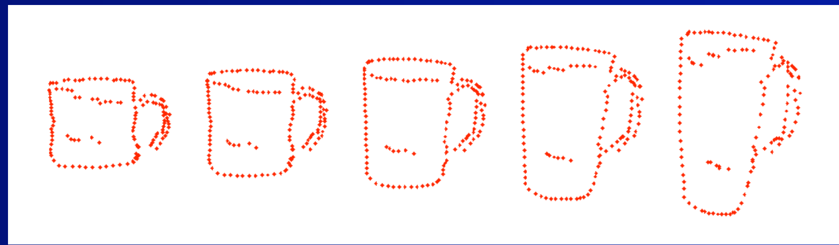
Deformation model
. top *n* eigenvectors covering 95% of variance
. associated eigenvalues λ_i (act as bounds)

⟶ *valid region* of shape space

Tim Cootes, *An introduction to Active Shape Models, 2000*

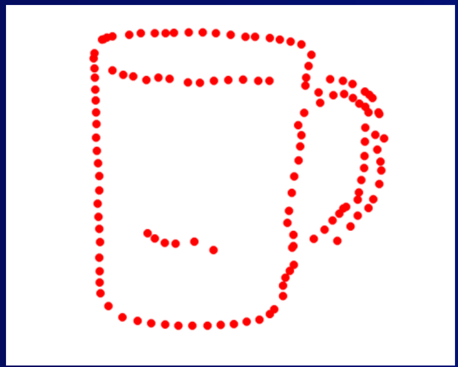
Learning completed !

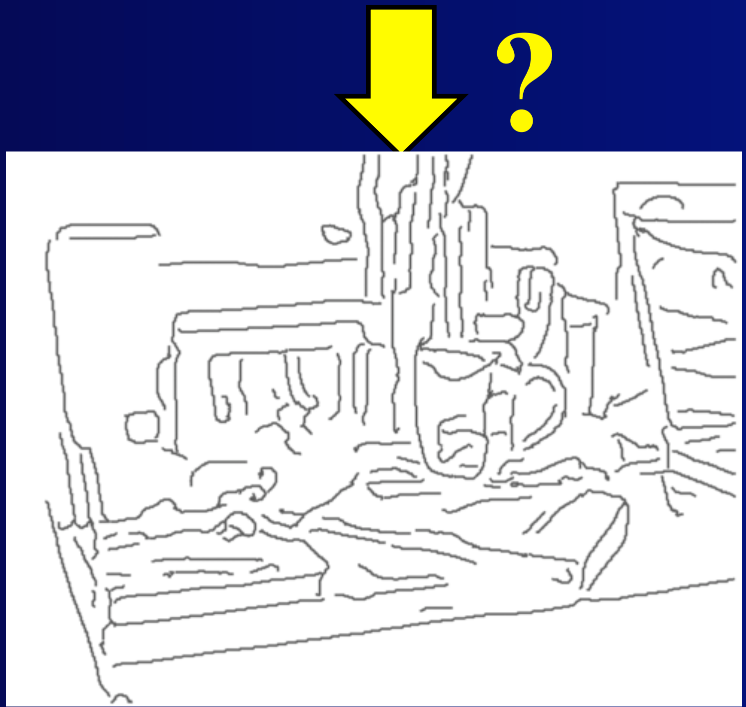




Automatic learning of shapes, correspondences, and deformations from unsegmented images

Object detection: overview





Goal

given a test image, localize class instances up to their boundaries

How ?

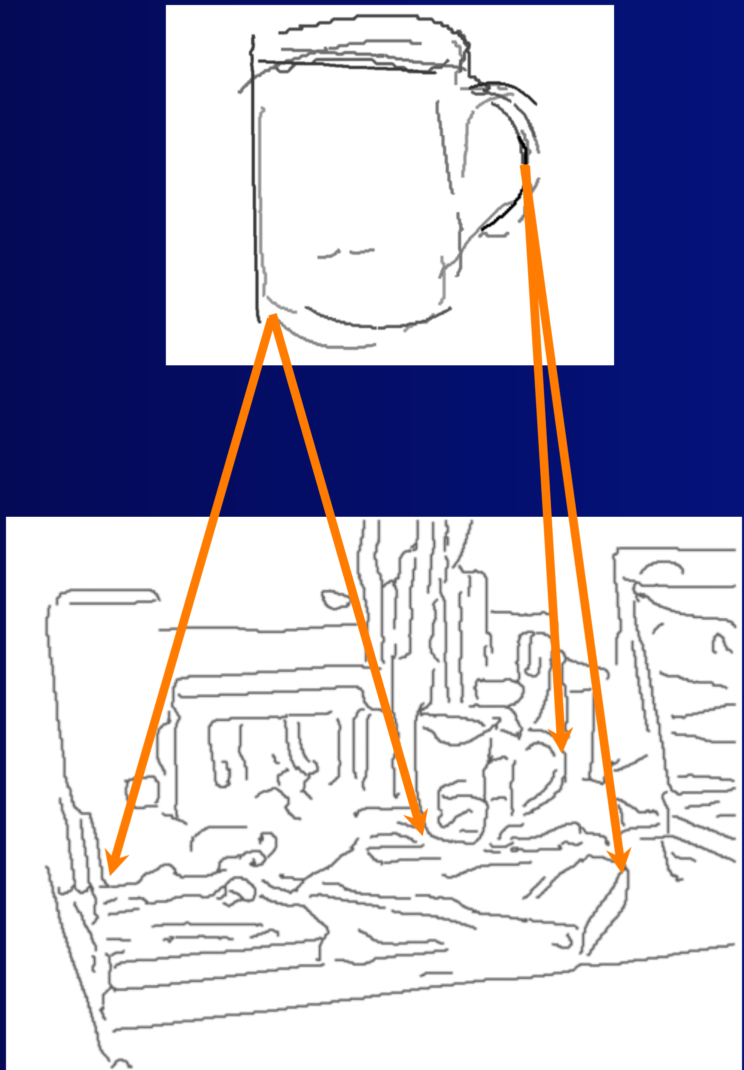
1. Hough voting over PAS matches
   ⟶ *rough* location+scale estimates

2. use to initialize TPS-RPM

   combination enables true pointwise shape matching to cluttered images

3. constrain TPS-RPM with learnt deformation model
   ⟶ better accuracy

Object detection: Hough voting



Algorithm

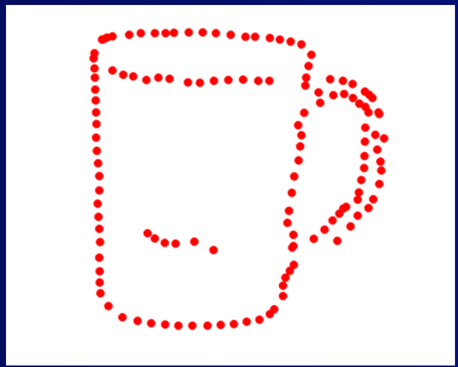
1. soft-match model parts to test PAS

2. each match
   → translation + scale change
   → vote in accumulator space

3. local maxima
   → rough estimates of object candidates

Leibe and Schiele, DAGM 2004; Shotton et al, ICCV 2005; Opelt et al. ECCV 2006

Object detection: Hough voting



Algorithm

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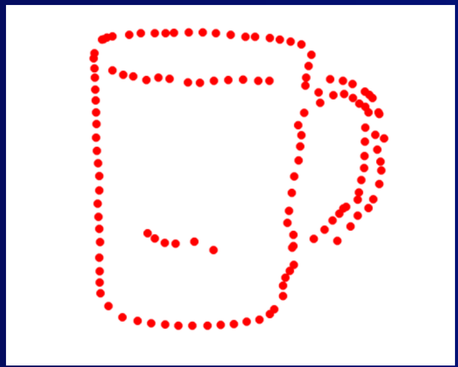
   → rough estimates of object candidates

initializations for shape matching !

Leibe and Schiele, DAGM 2004; Shotton et al, ICCV 2005; Opelt et al. ECCV 2006

Object detection: Hough voting



Remember … soft !

- vote $\propto$ shape similarity
- vote $\propto$ edge strength of test PAS
- vote $\propto$ strength of model part
- spread vote to neighboring location and scale bins

Object detection: shape matching by TPS-RPM

Initialize
get point sets V (model) and X (edge points)

Goal
find correspondences M &
non-rigid TPS mapping

M = (|X|+1)x(|V|+1) soft-assign matrix

Algorithm

1. Update M based on
   dist(TPS,X) + orient(TPS,X) + strength(X)
2. Update TPS:
   - Y = MX
   - fit regularized TPS to V⟷Y

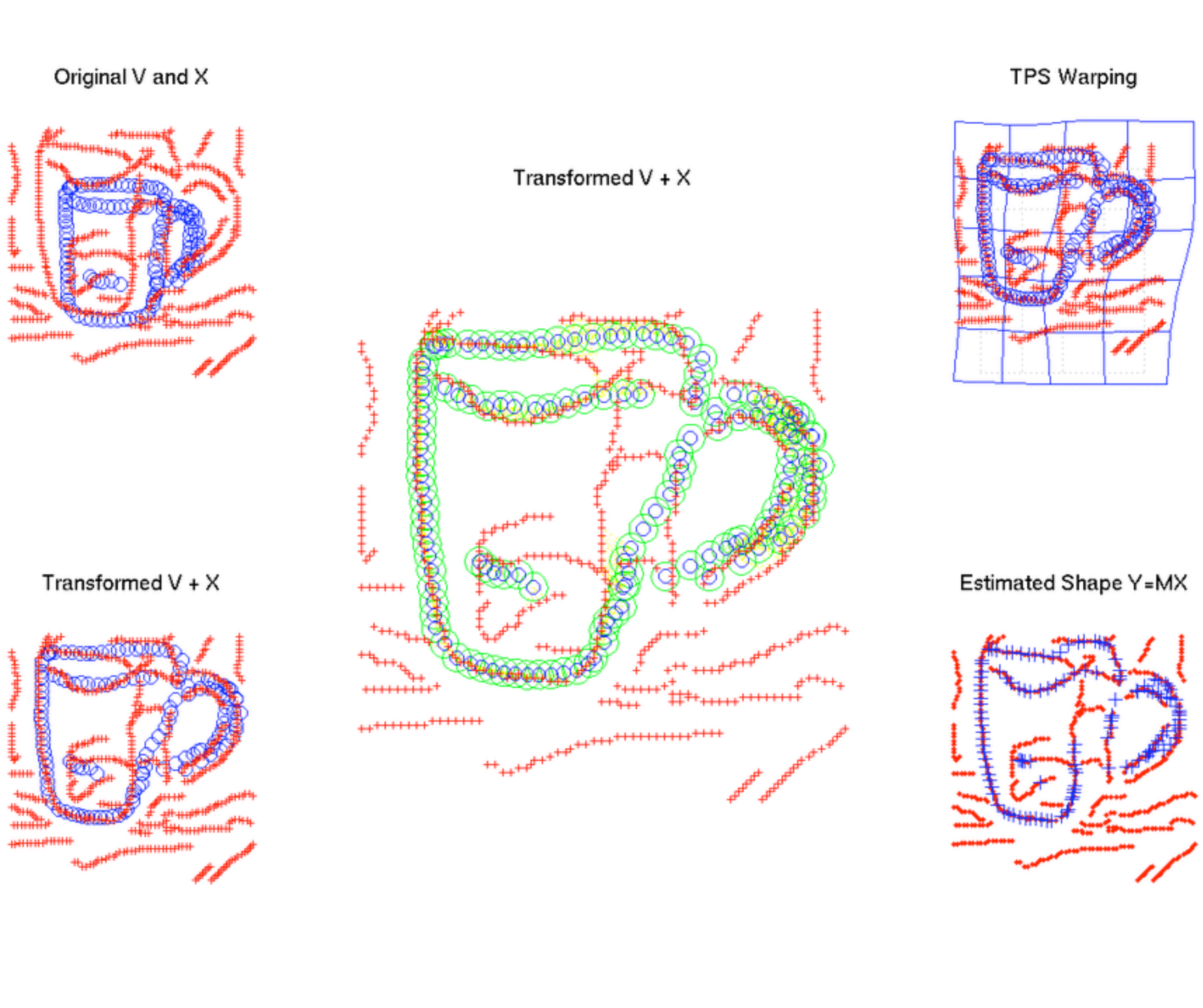
Deterministic annealing:
iterate with T decreasing

→ M less fuzzy (looks closer)

→ TPS more deformable

Chui and Rangarajan, *A new point matching algorithm for non-rigid registration*, CVIU 2003

TPS-RPM in action !



Object detection: constrained TPS-RPM

Output of TPS-RPM

nice, but sometimes inaccurate
or even not mug-like

Why ?

generic TPS deformation model
(prefers smoother transforms)

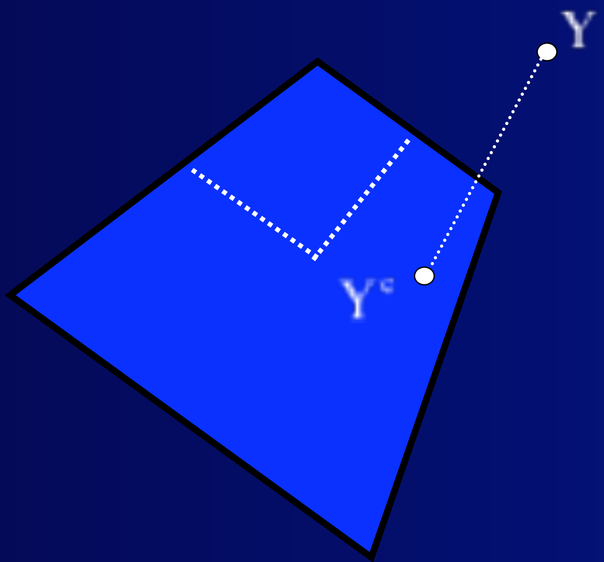
Constrained shape matching

constrain TPS-RPM by learnt
class-specific deformation model

+ only shapes similar to class members

+ improve detection accuracy

Object detection: constrained TPS-RPM



General idea

constrain optimization to explore only region of shape space spanned by training examples

How to modify TPS-RPM ?

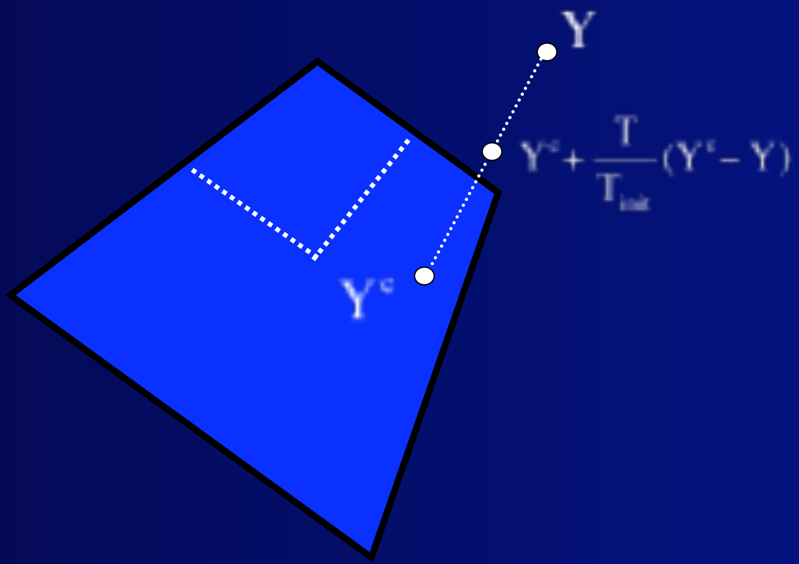
1. Update M

2. Update TPS:

   - $Y = MX$
   - $Y \leftarrow Y^c$
   - fit regularized TPS to $V \longleftrightarrow Y$

hard constraint,
sometimes too restrictive

Object detection: constrained TPS-RPM



General idea

constrain optimization to explore only region of shape space spanned by training examples

Soft constraint variant

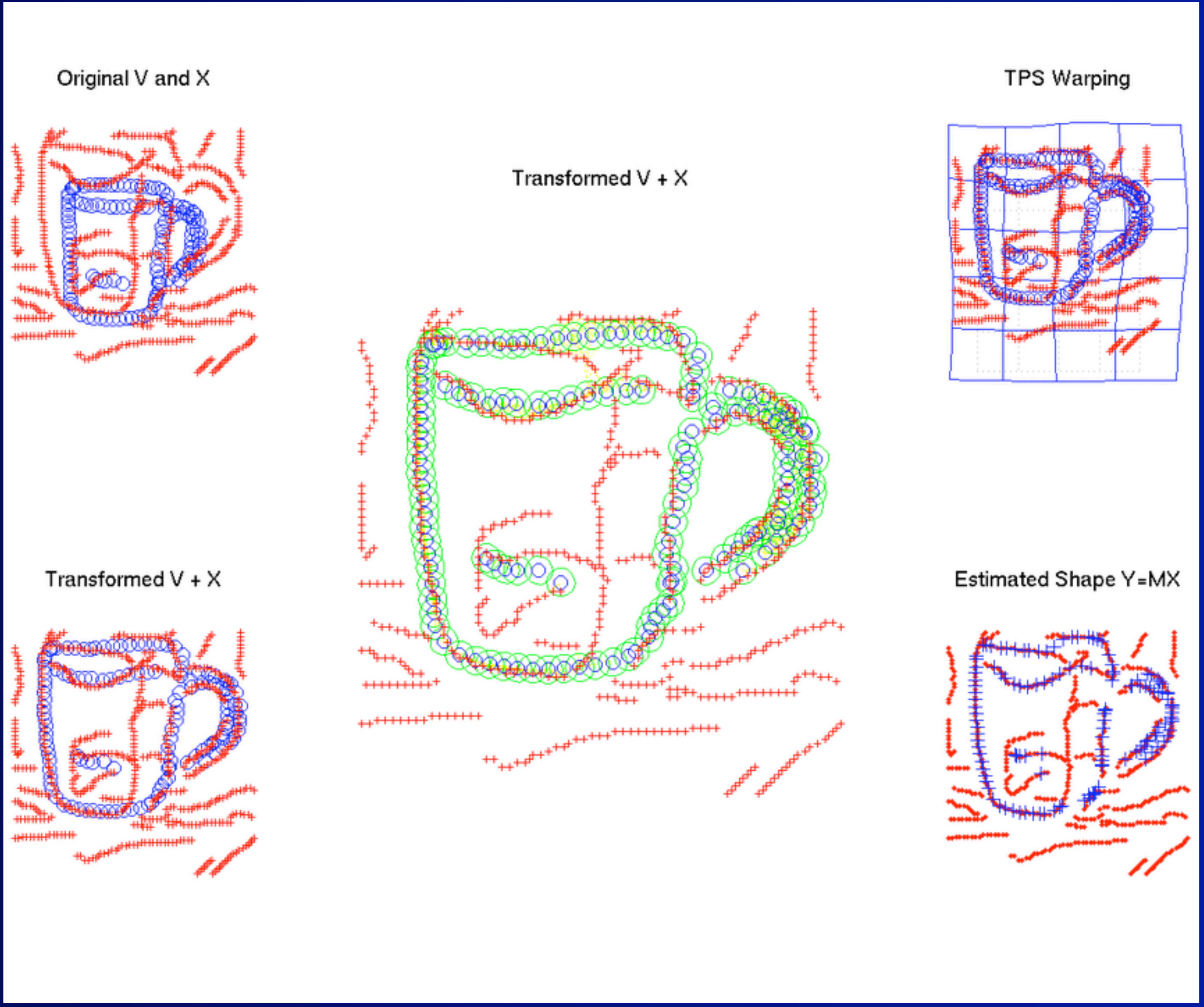
1. Update M

2. Update TPS:

- $Y = MX$
- $Y \leftarrow Y^c + \frac{T}{T_{init}}(Y^c - Y)$
- fit regularized TPS to $V \longleftrightarrow Y$

soft constraint,
Y is *attracted* by the valid region

Soft constrained TPS-RPM in action !



Object detection: constrained TPS-RPM

Soft constrained TPS-RPM

+ shapes fit data more accurately

+ shapes resemble class members

+ in spirit of deterministic annealing !

+ truly alters the search
(not fix a posteriori)

Does it really make a difference ?

when it does, it's really noticeable
(about 1 in 4 cases)

Datasets: ETHZ Shape Classes

- 255 images from *Google-images,* and *Flickr*
  - uncontrolled conditions
  - variety: indoor, outdoor, natural, man-made, …
  - wide range of scales (factor 4 for swans, factor 6 for apple-logos)
- all parameters are kept fixed for all experiments
- training images: 5x random half of positive; test images: *all* non-train

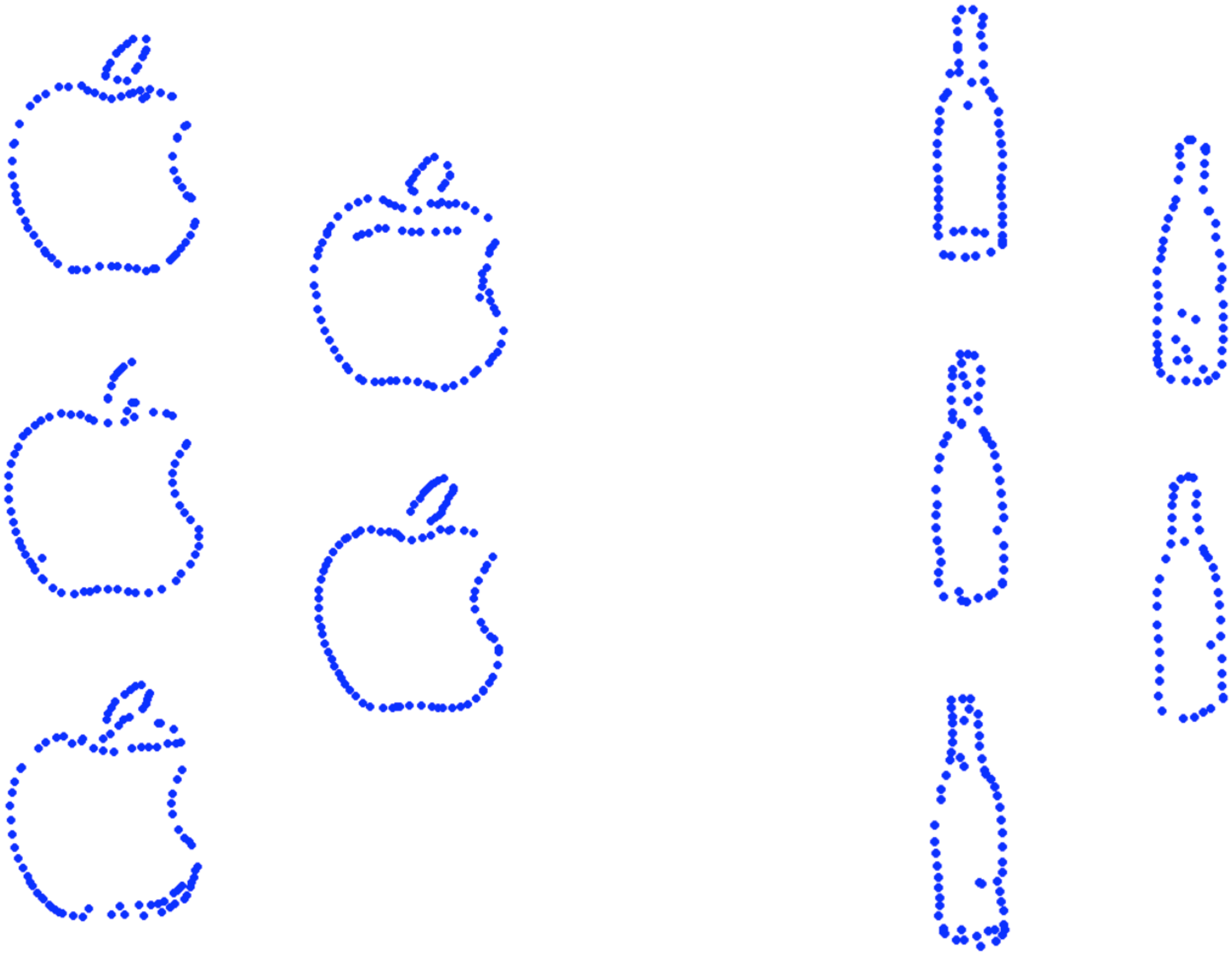
Datasets: INRIA Horses

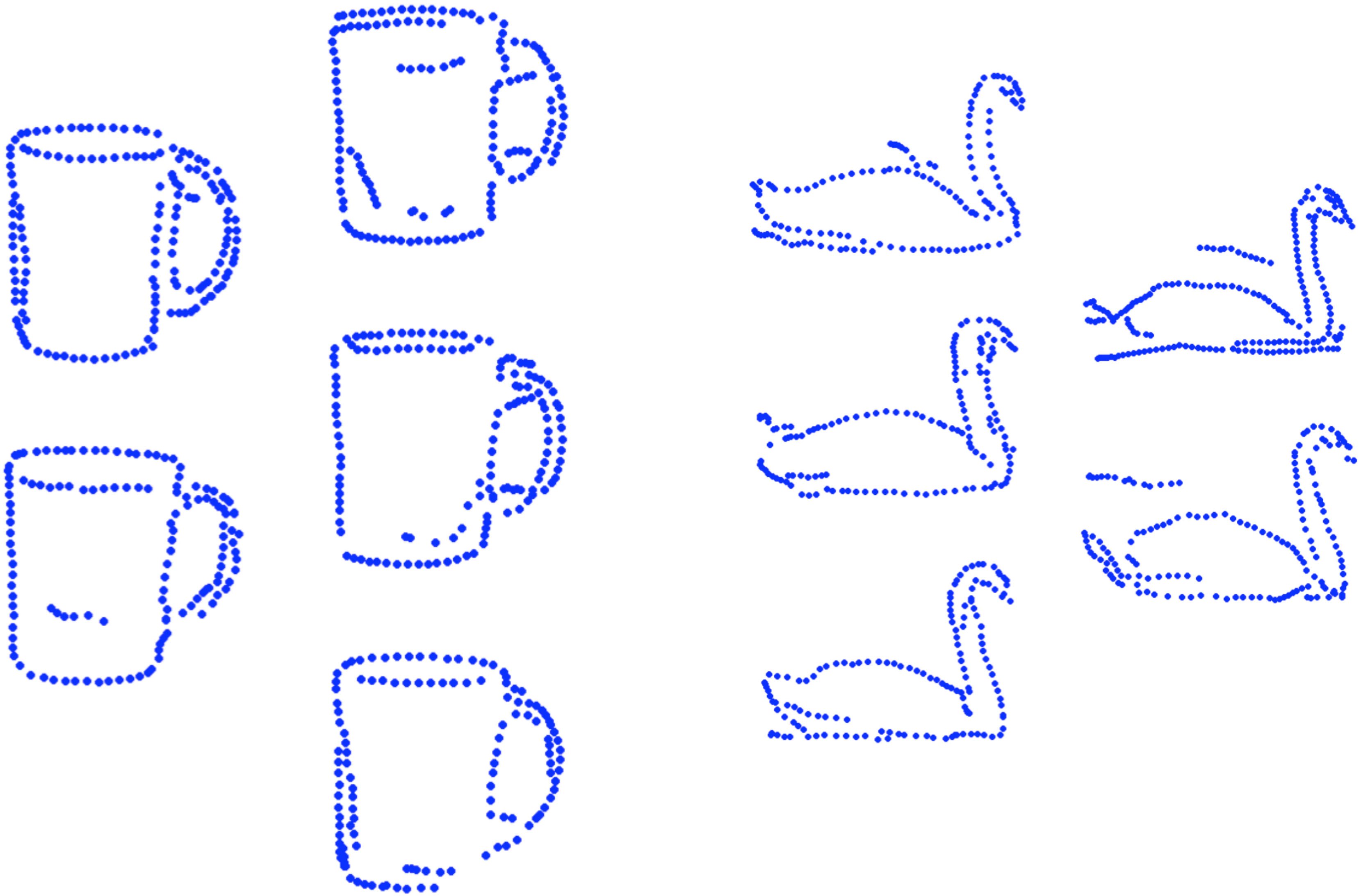
- 170 horse images + 170 non-horse ones
  - clutter, scale changes, various poses

- all parameters are kept fixed for all experiments
- training images: 5x random 50; test images: all non-train images

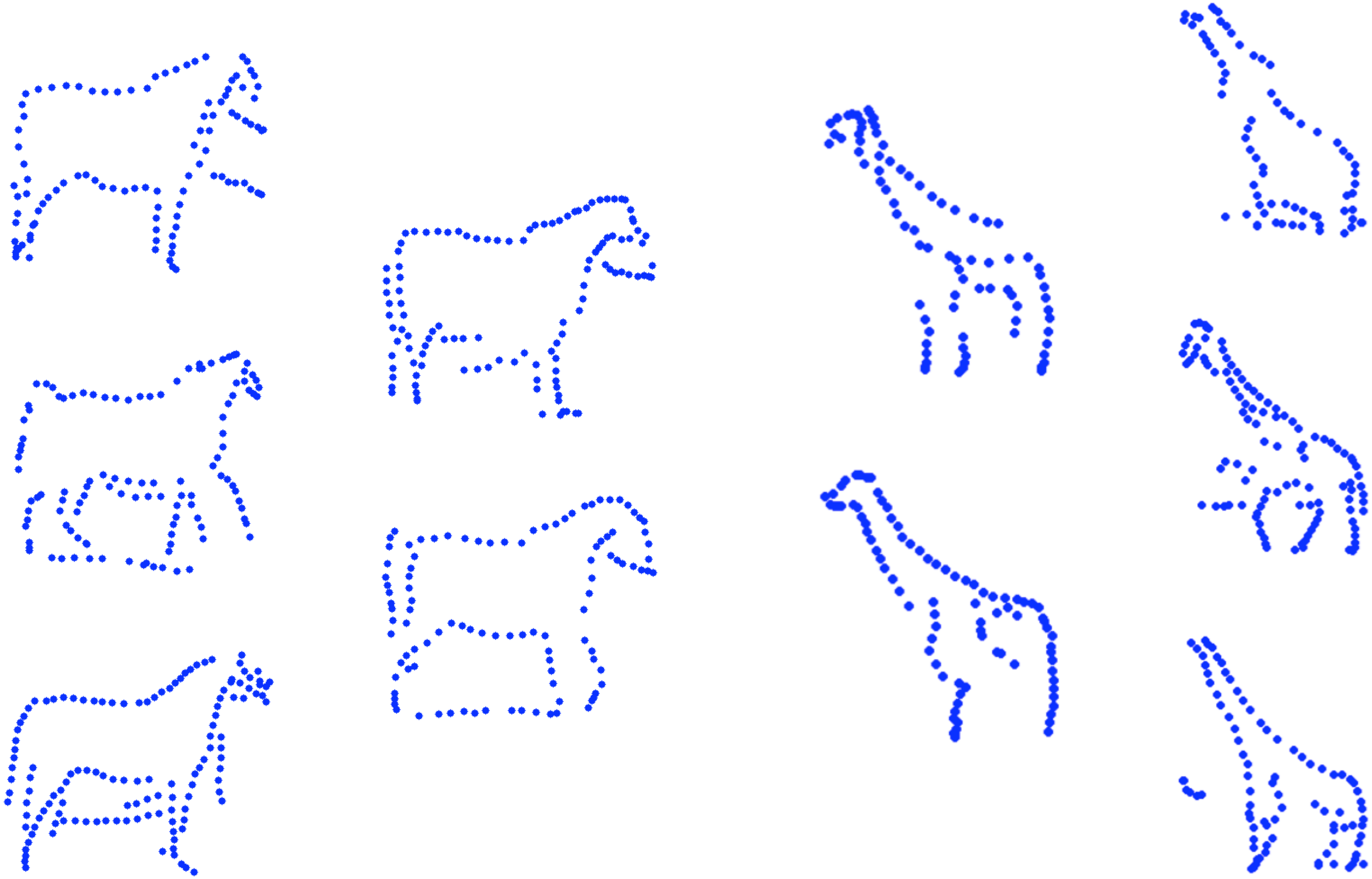
Results: all learned models



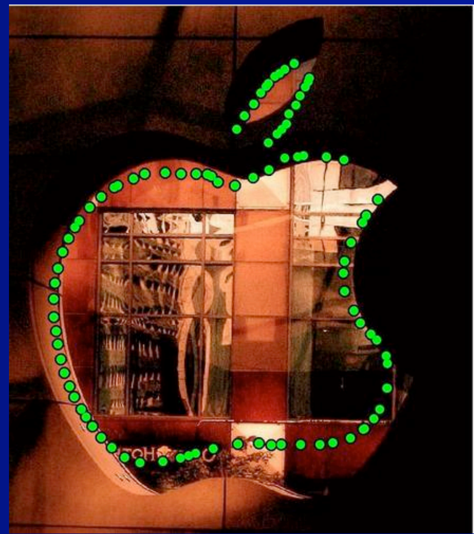
Results: all learned models

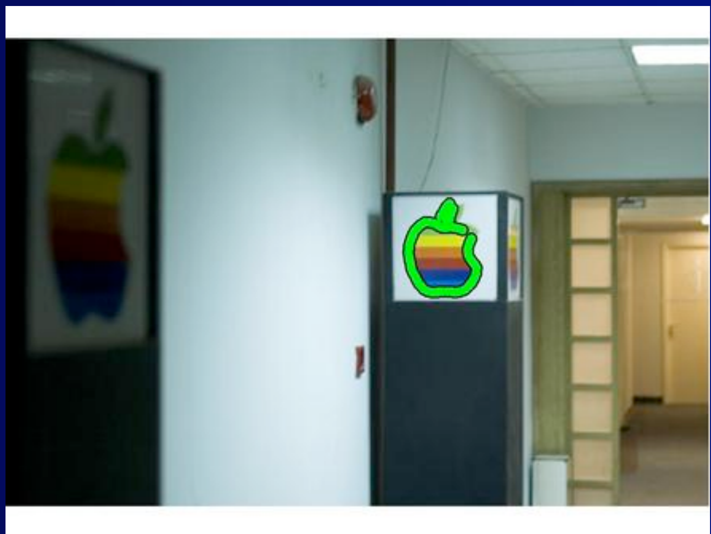


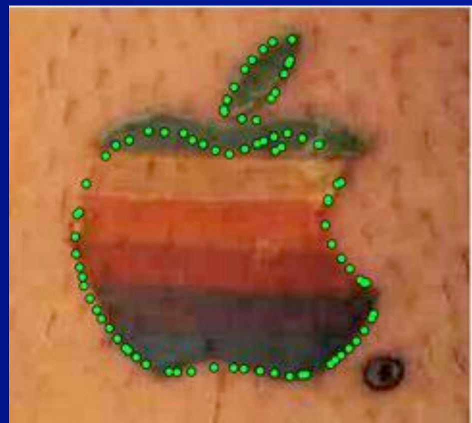
Results: all learned models



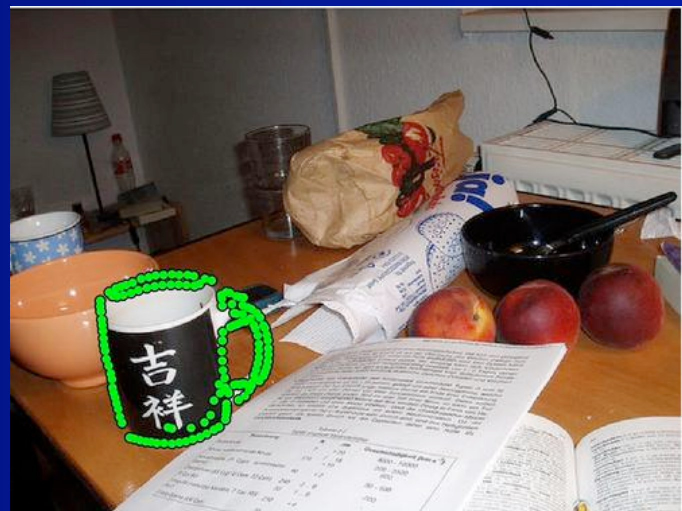
Results: apple logos



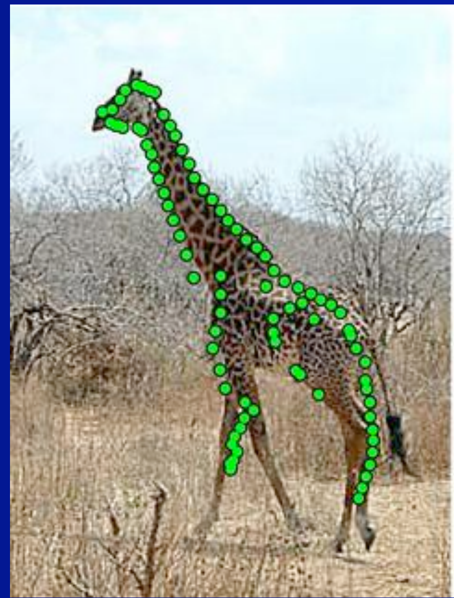




Results: mugs

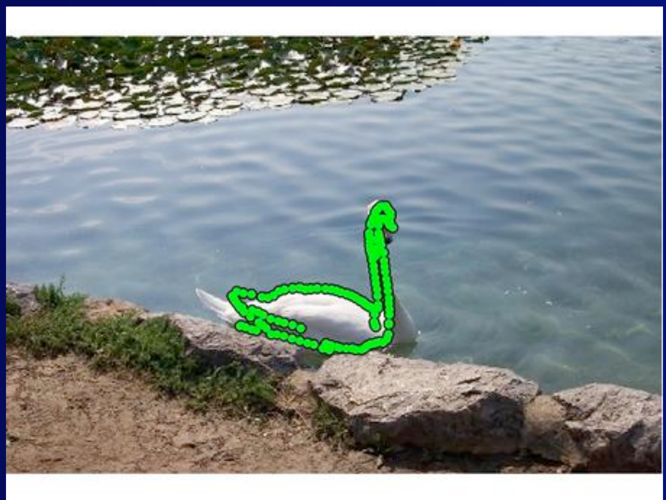


Results: giraffes

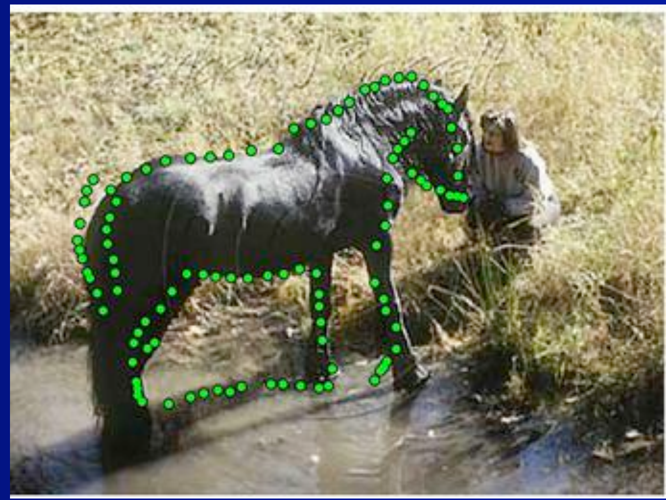


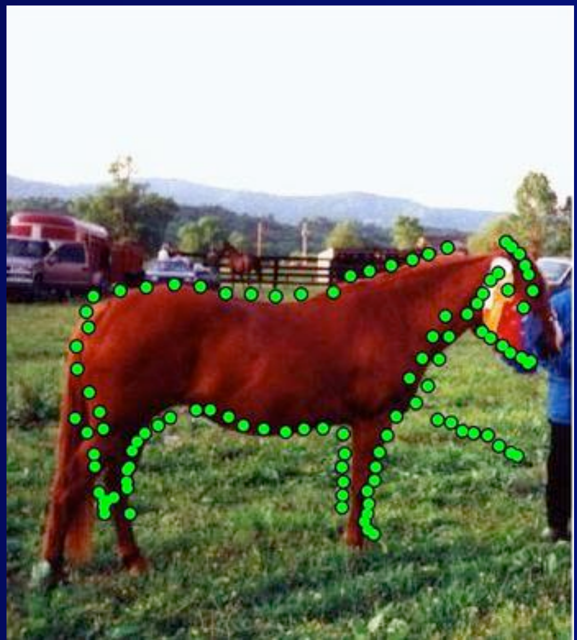
Results: bottles

Results: swans



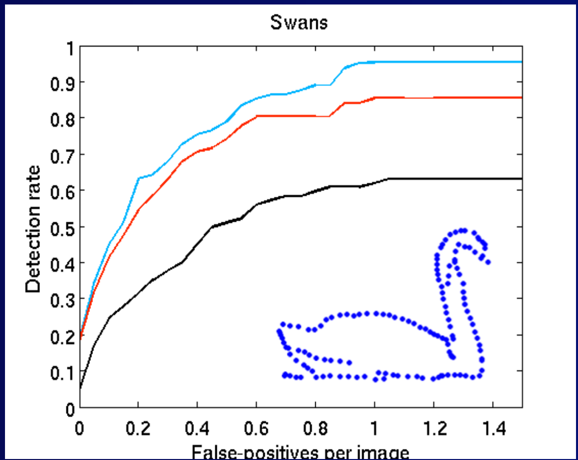
Results: horses



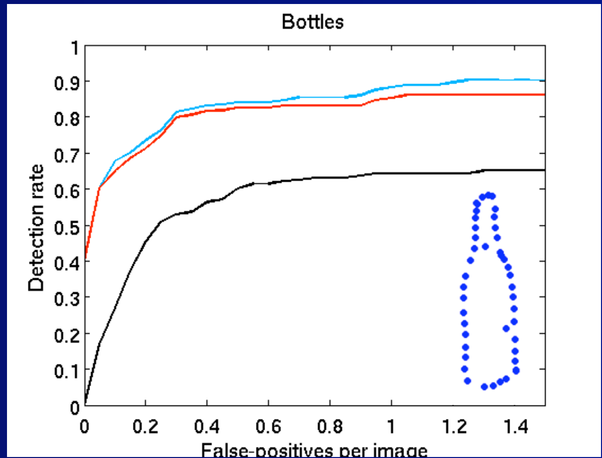


Results: detection-rate vs false-positives per image

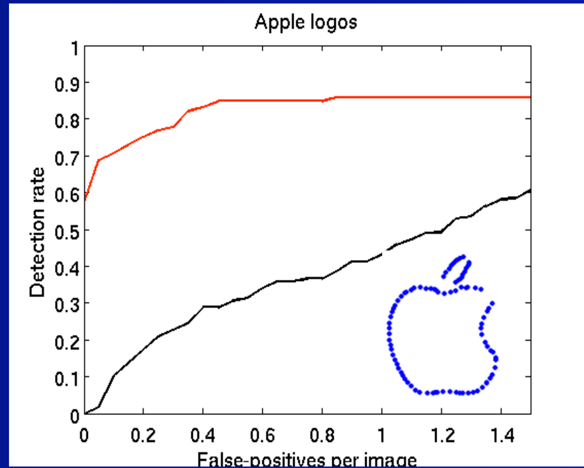
accuracy: 3.0



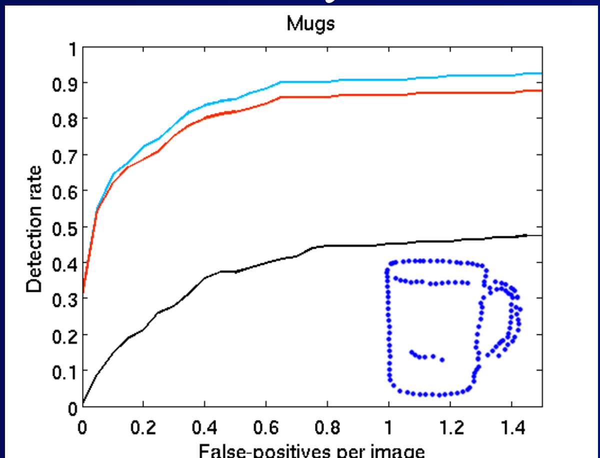
accuracy: 2.4



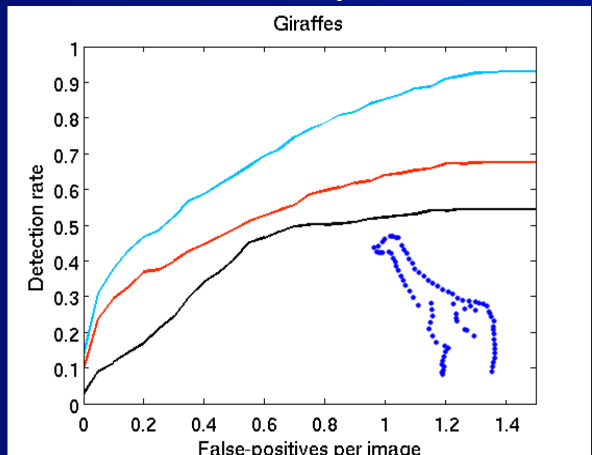
accuracy: 1.5



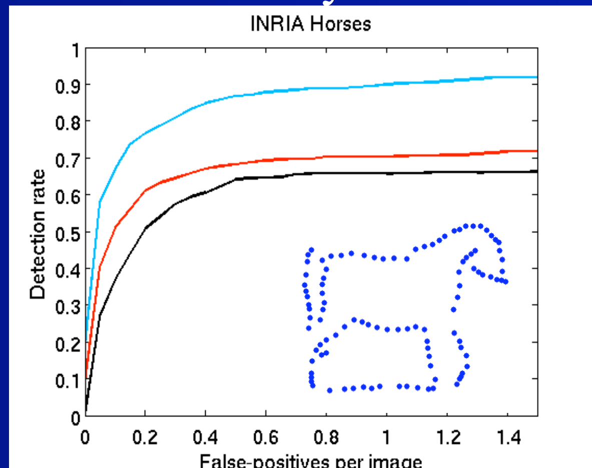
accuracy: 3.1



accuracy: 3.5



accuracy: 5.4

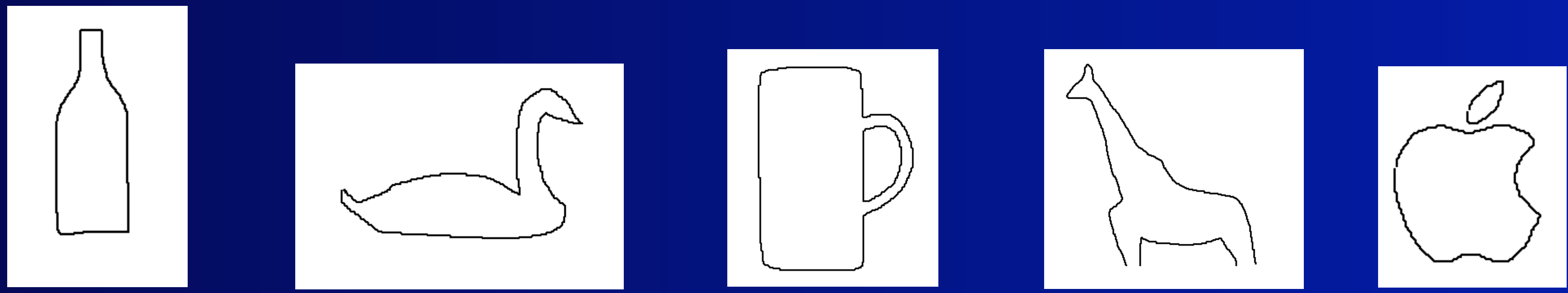


full system (>20% intersection)

full system (PASCAL: $\cap / \cup$ >50%)

Hough alone (PASCAL)

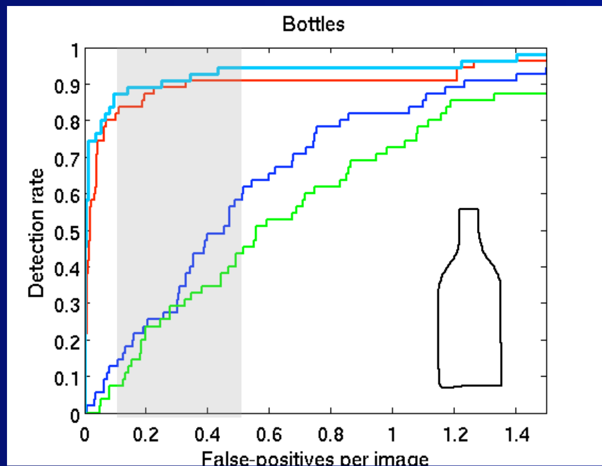
Results: Hand-drawings

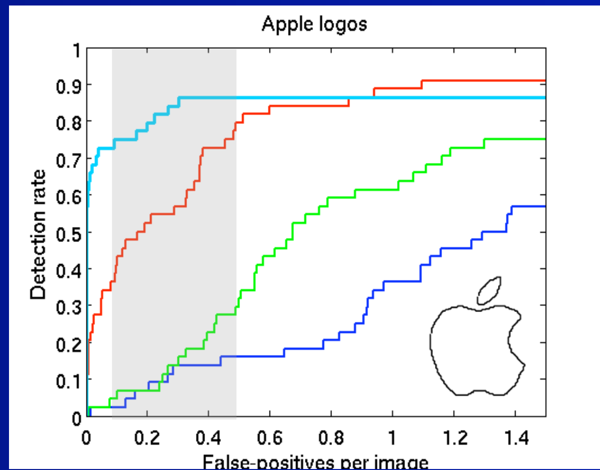


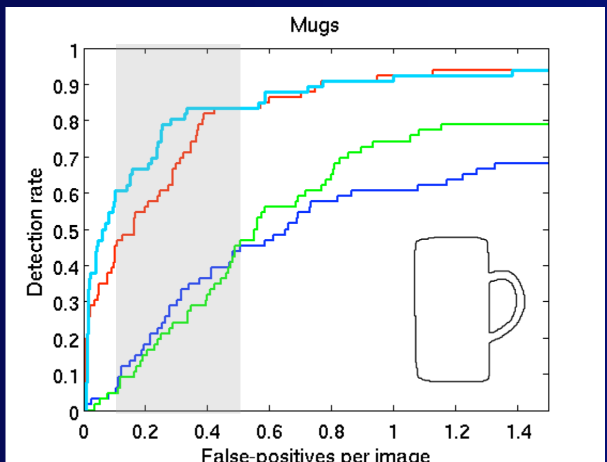
Same protocol as Ferrari et al, ECCV 2006:
match each hand-drawing to all 255 test images

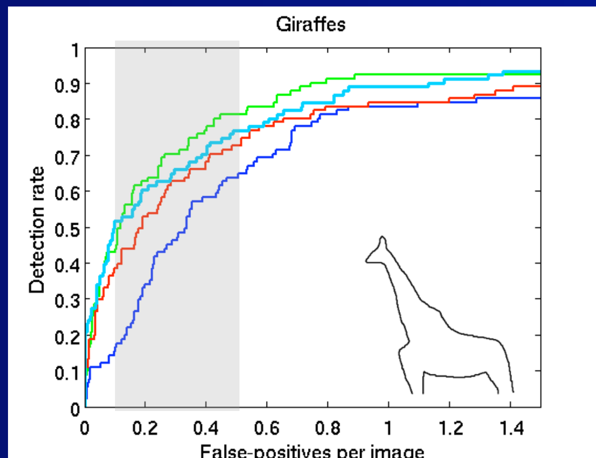
Results: detection-rate vs false-positives per image

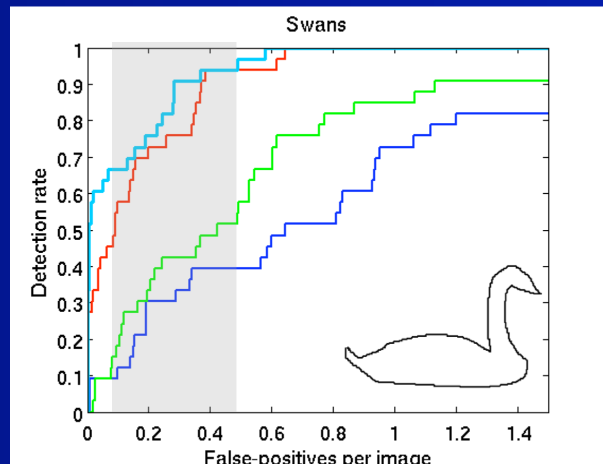
- our approach
- Ferrari, ECCV06
- chamfer (with orientation planes)
- chamfer (no orientation planes)











Conclusions

1. learning shape models from images

2. matching them to new cluttered images

+ detect object boundaries while needing only BBs for training

+ effective also with hand-drawings as models

+ deals with extensive clutter, shape variability, and large scale changes

- can't learn highly deformable classes (e.g. jellyfish)

- model quality drops with very high training clutter/fragmentation (giraffes)

Overview

- Localization with shape-based descriptors
- Learning deformable shape models
- *Segmentation, pixel-level classification*

Image segmentation

The goals of segmentation

- Separate image into coherent “objects”
  - “Bottom-up” or “top-down” process?
  - Supervised or unsupervised?

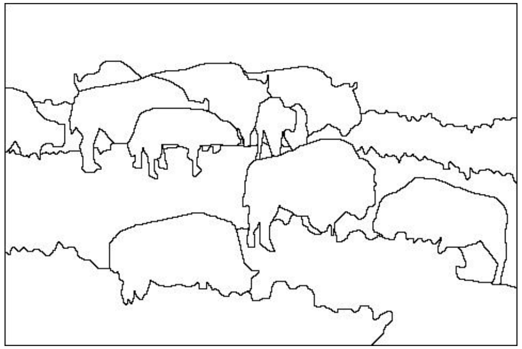
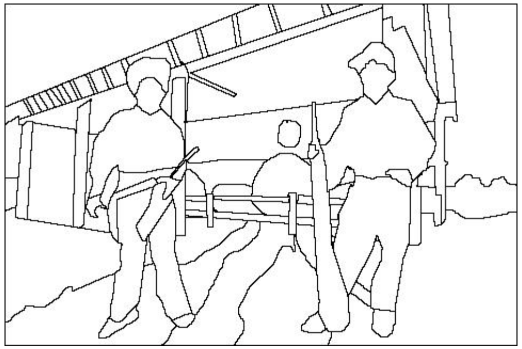



image human segmentation

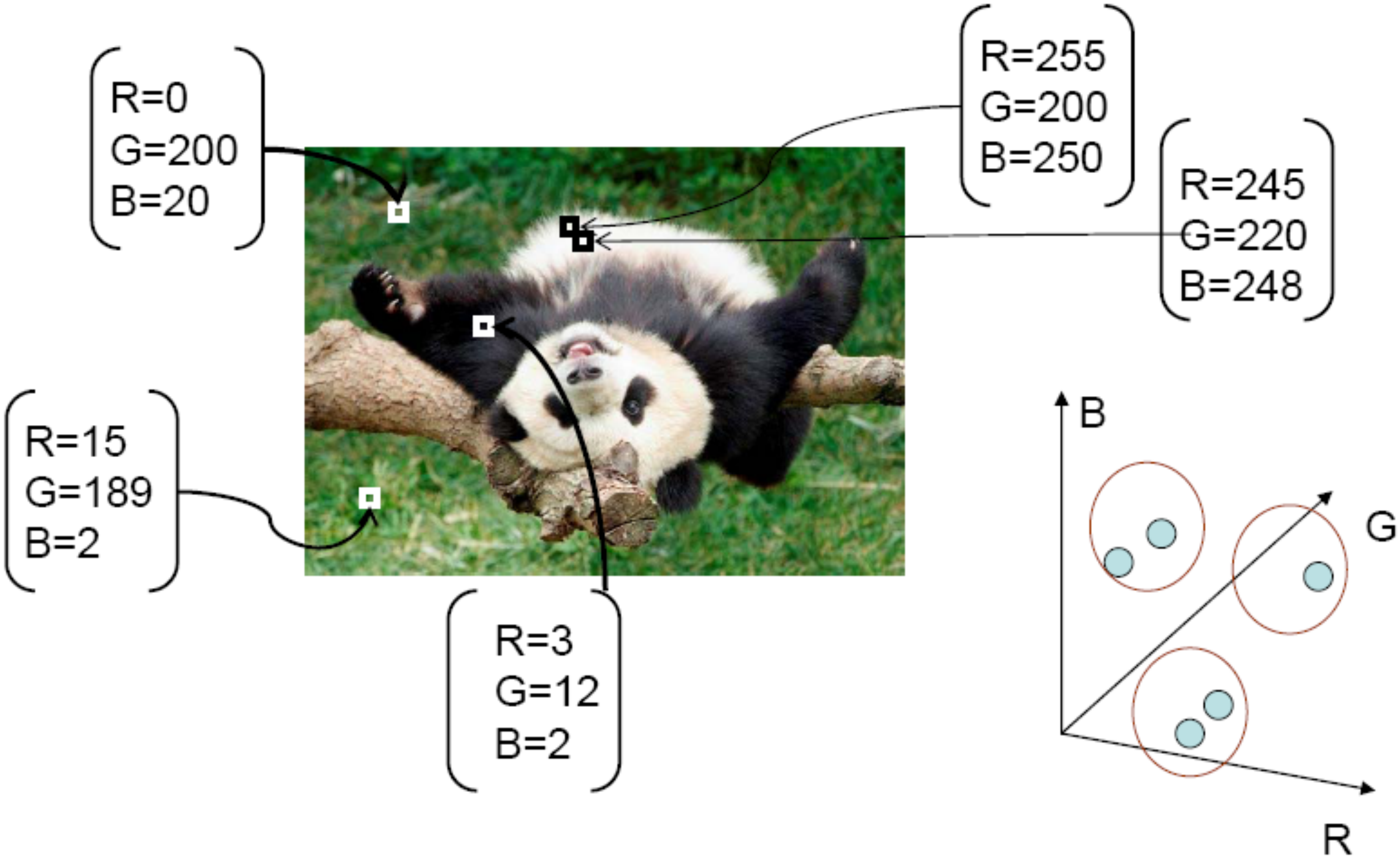



Berkeley segmentation database:

http://www.eecs.berkeley.edu/Research/Projects/CS/vision/grouping/segbench/

Segmentation as clustering

- Cluster similar pixels (features) together



Source: K. Grauman

Segmentation as clustering

- K-means clustering based on intensity or color is essentially vector quantization of the image attributes
  - Clusters don’t have to be spatially coherent

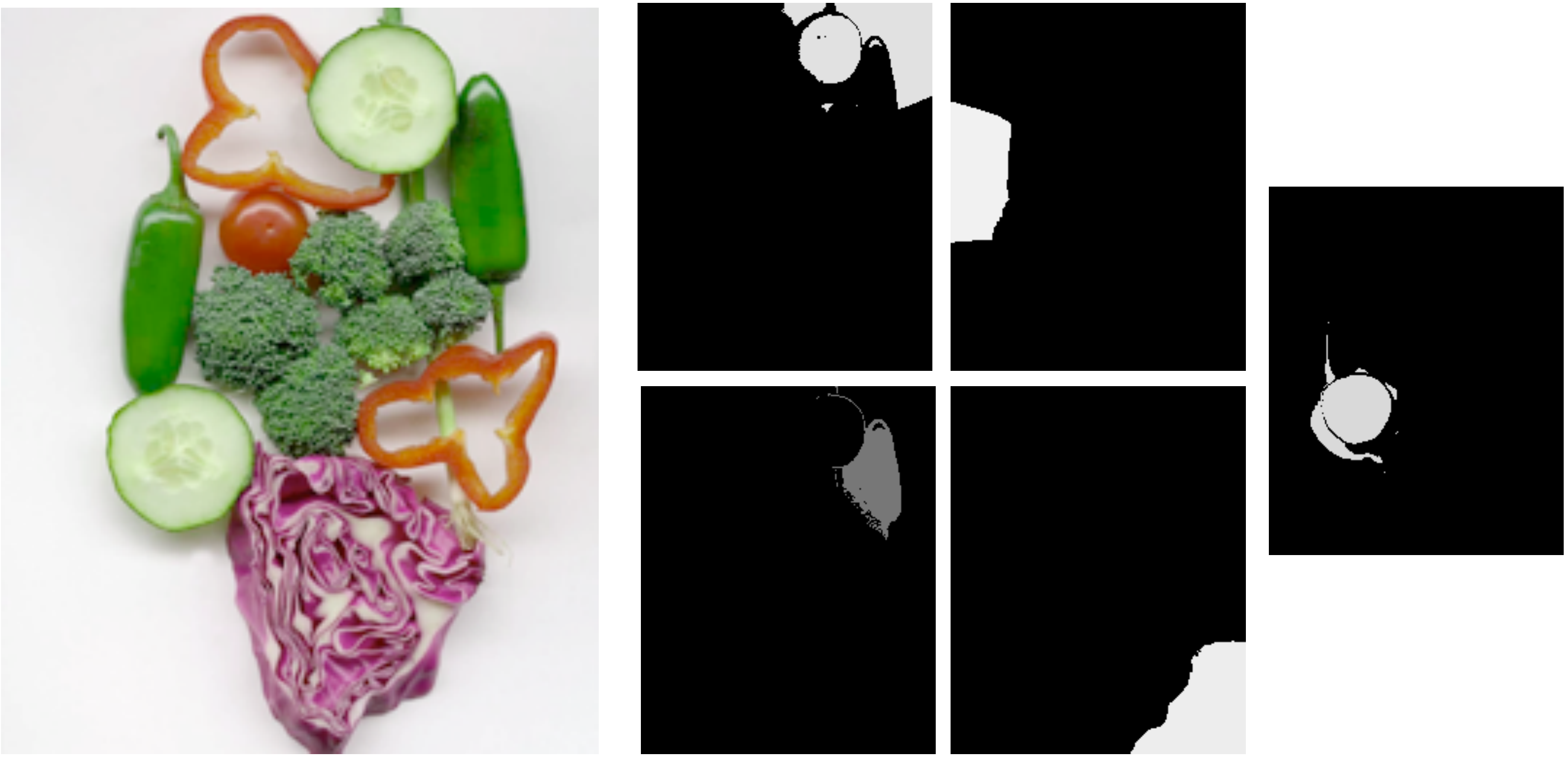
Image

Intensity-based clusters

Color-based clusters

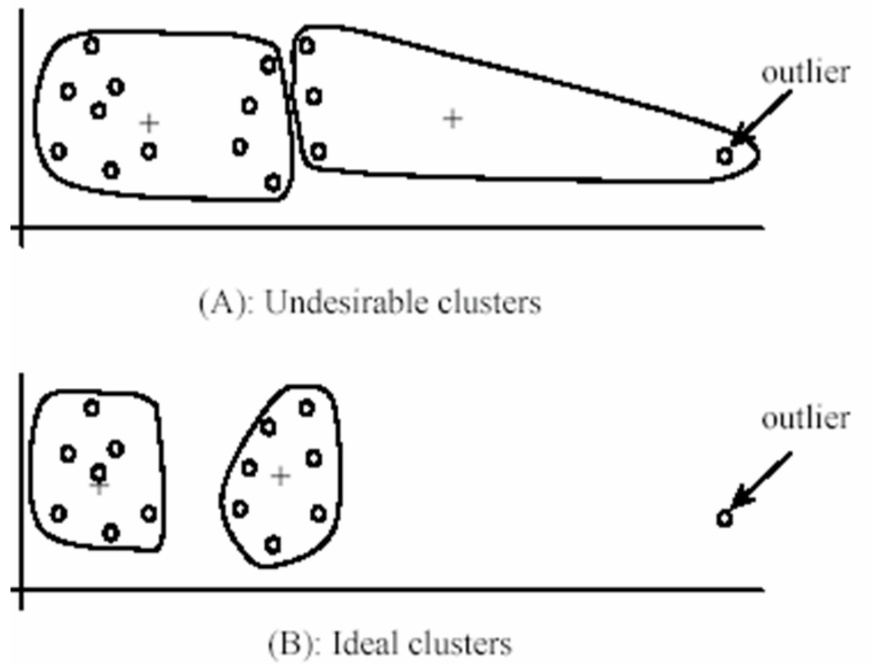
Segmentation as clustering

- Clustering based on (r,g,b,x,y) values enforces more spatial coherence



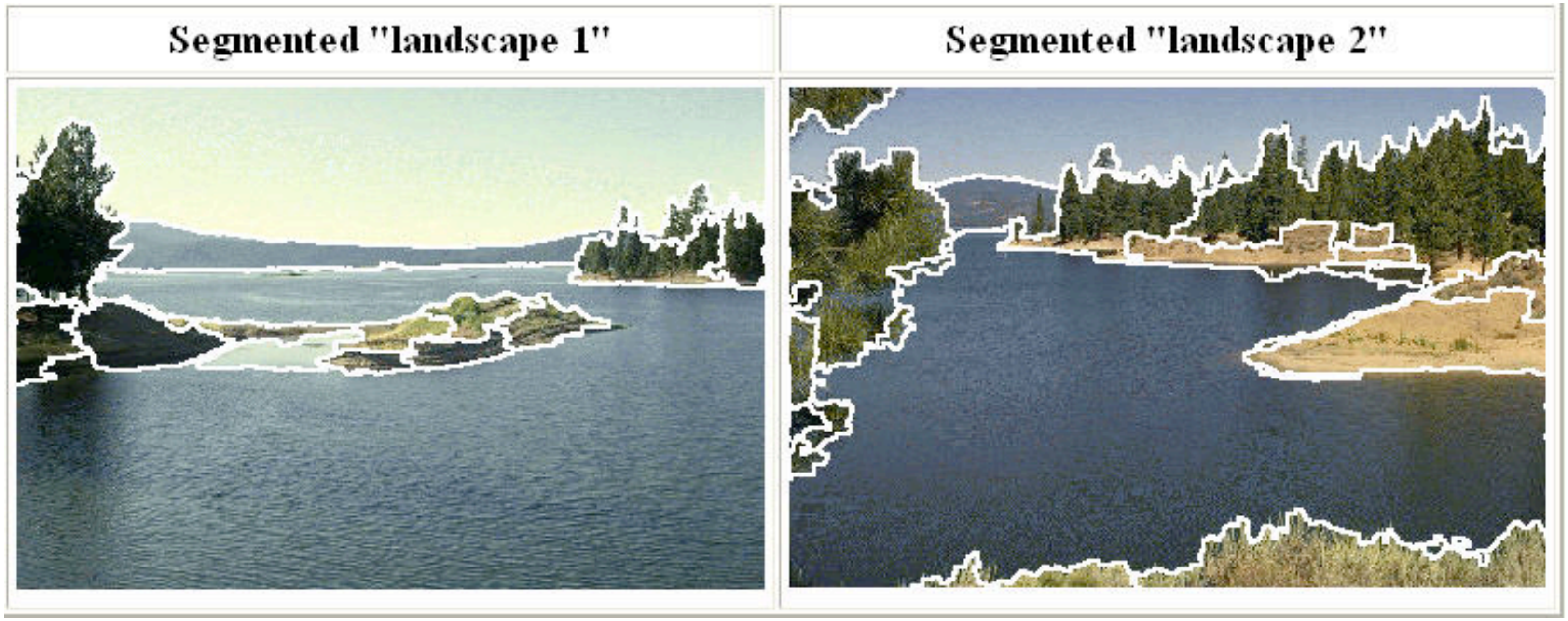
K-Means for segmentation

- Pros
  - Very simple method
  - Converges to a local minimum of the error function
- Cons
  - Memory-intensive
  - Need to pick K
  - Sensitive to initialization
  - Sensitive to outliers
  - Only finds “spherical” clusters



Mean shift clustering and segmentation

- An advanced and versatile technique for clustering-based segmentation



http://www.caip.rutgers.edu/~comanici/MSPAMI/msPamiResults.html

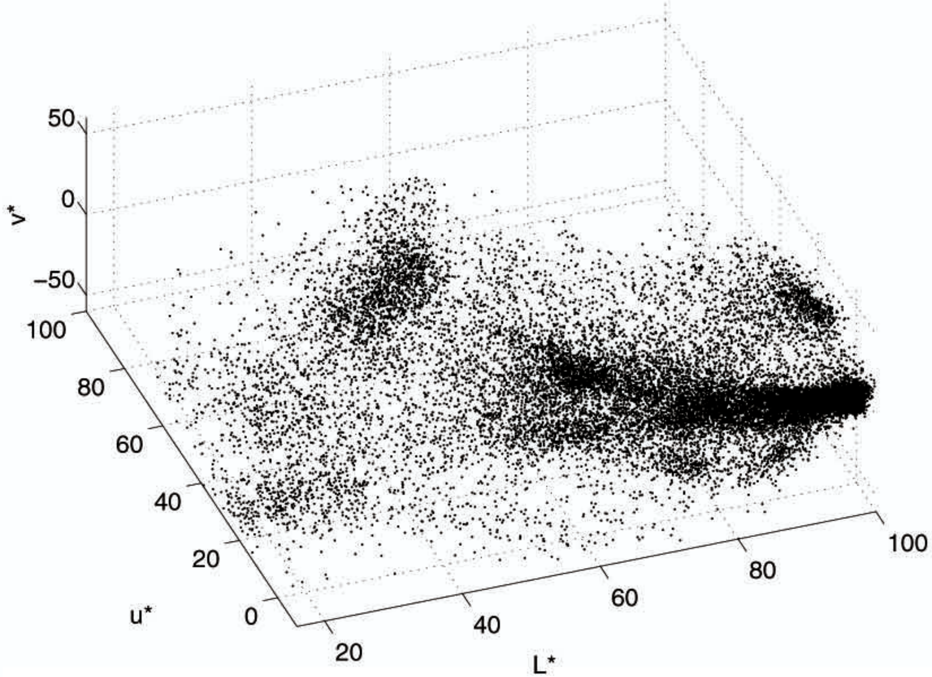
D. Comaniciu and P. Meer,
Mean Shift: A Robust Approach toward Feature Space Analysis, PAMI 2002.

Mean shift algorithm

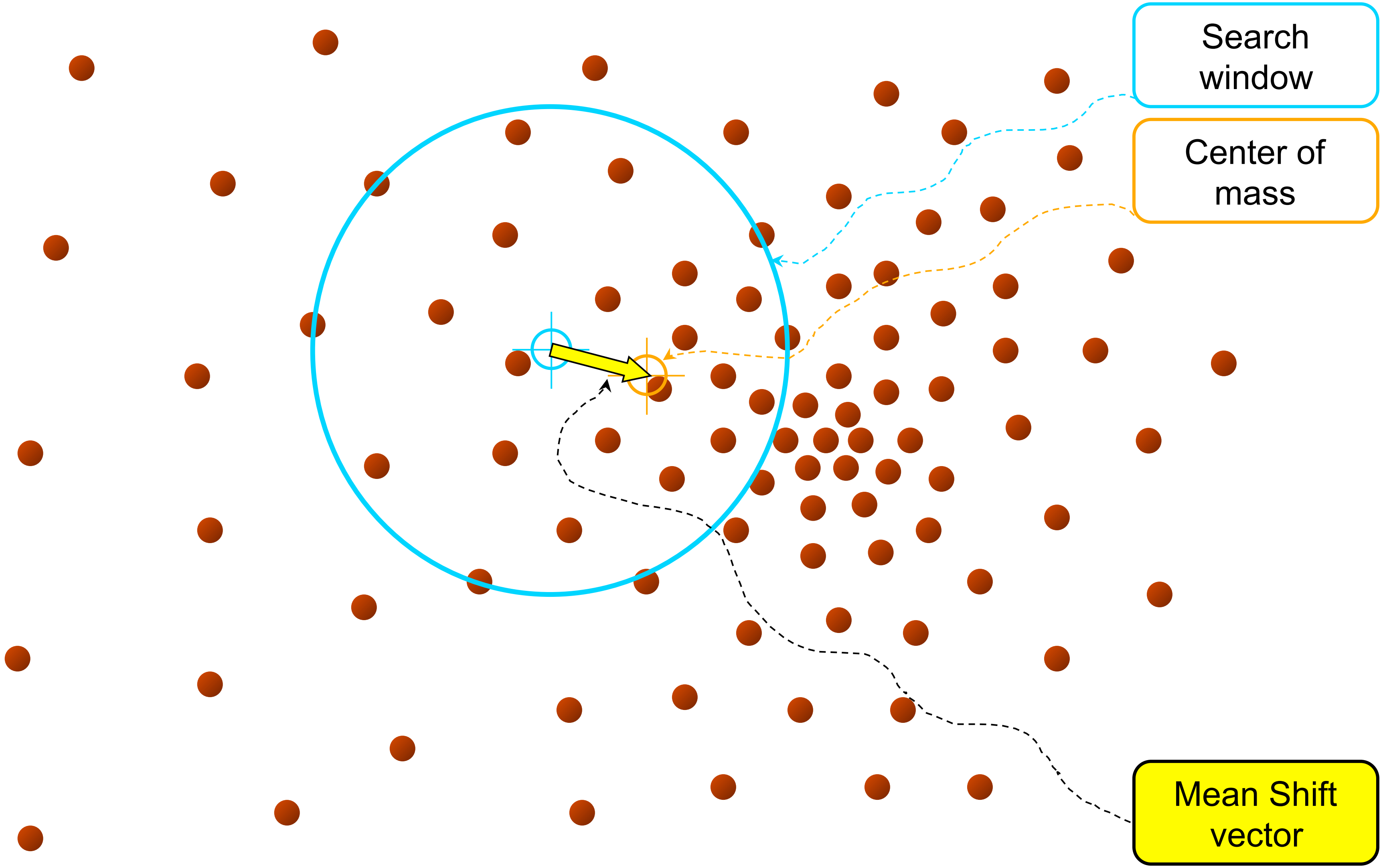
- The mean shift algorithm seeks *modes* or local maxima of density in the feature space

image

Feature space (L*u*v* color values)

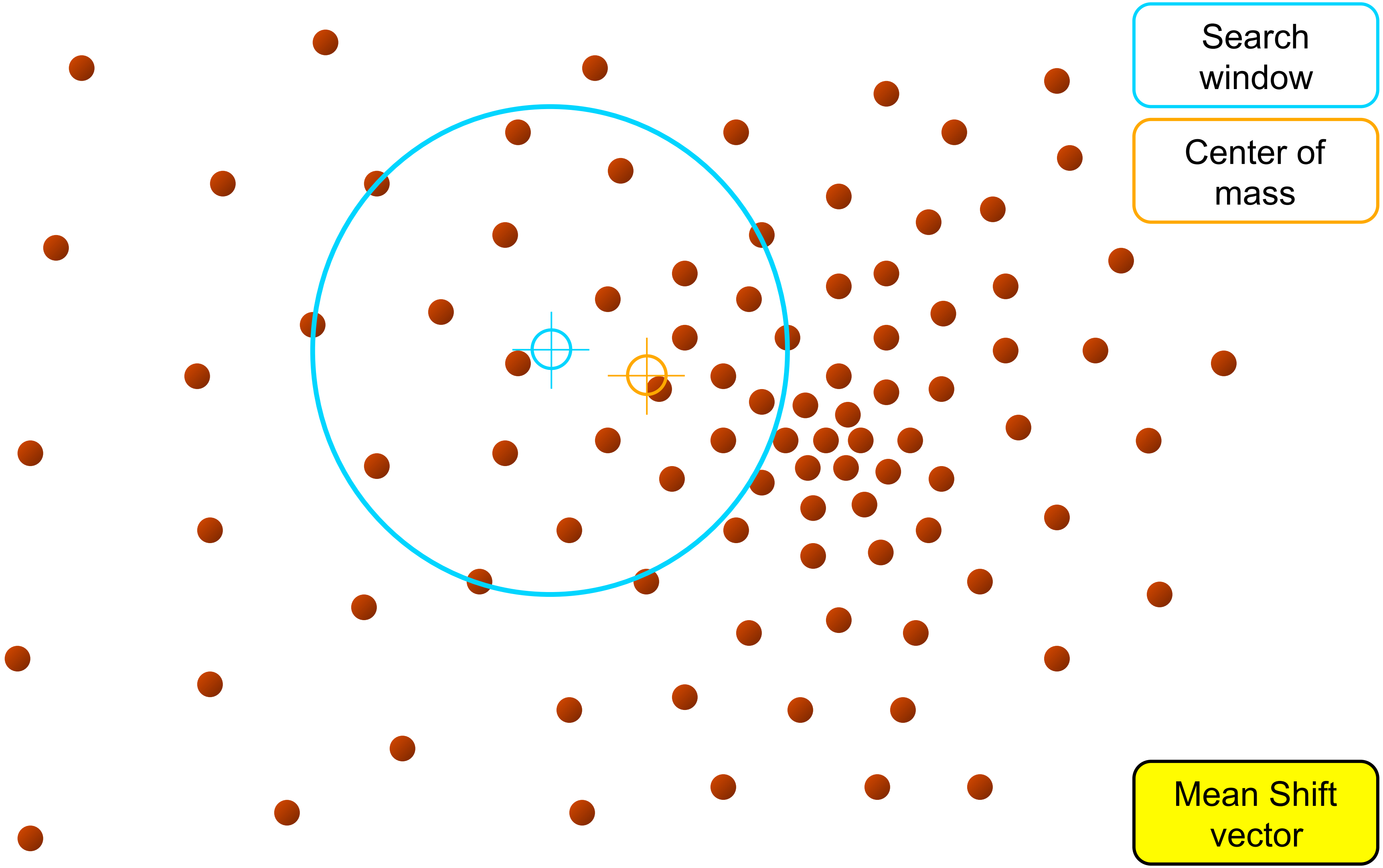


Mean shift



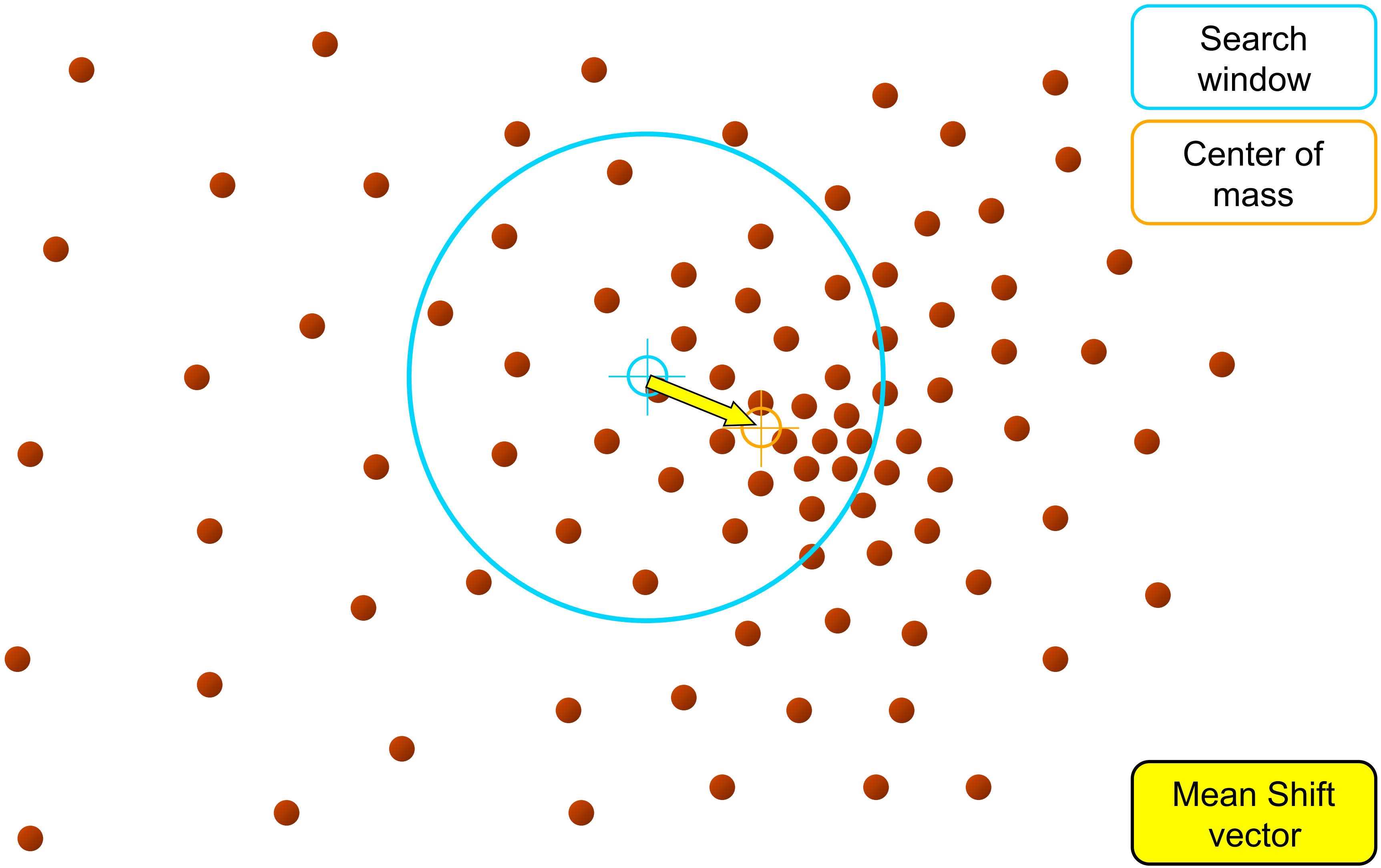
Slide by Y. Ukrainitz & B. Sarel

Mean shift



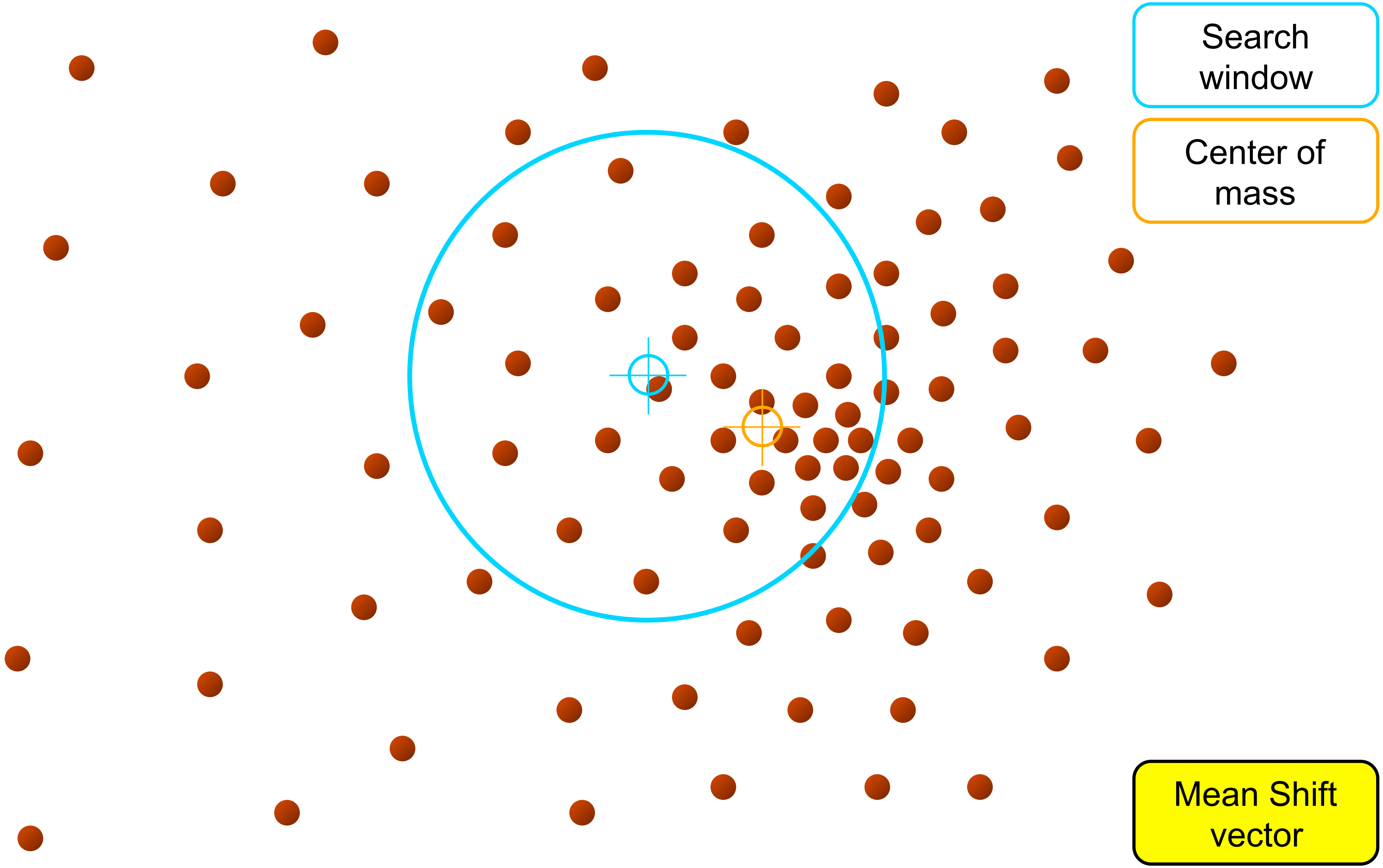
Slide by Y. Ukrainitz & B. Sarel

Mean shift



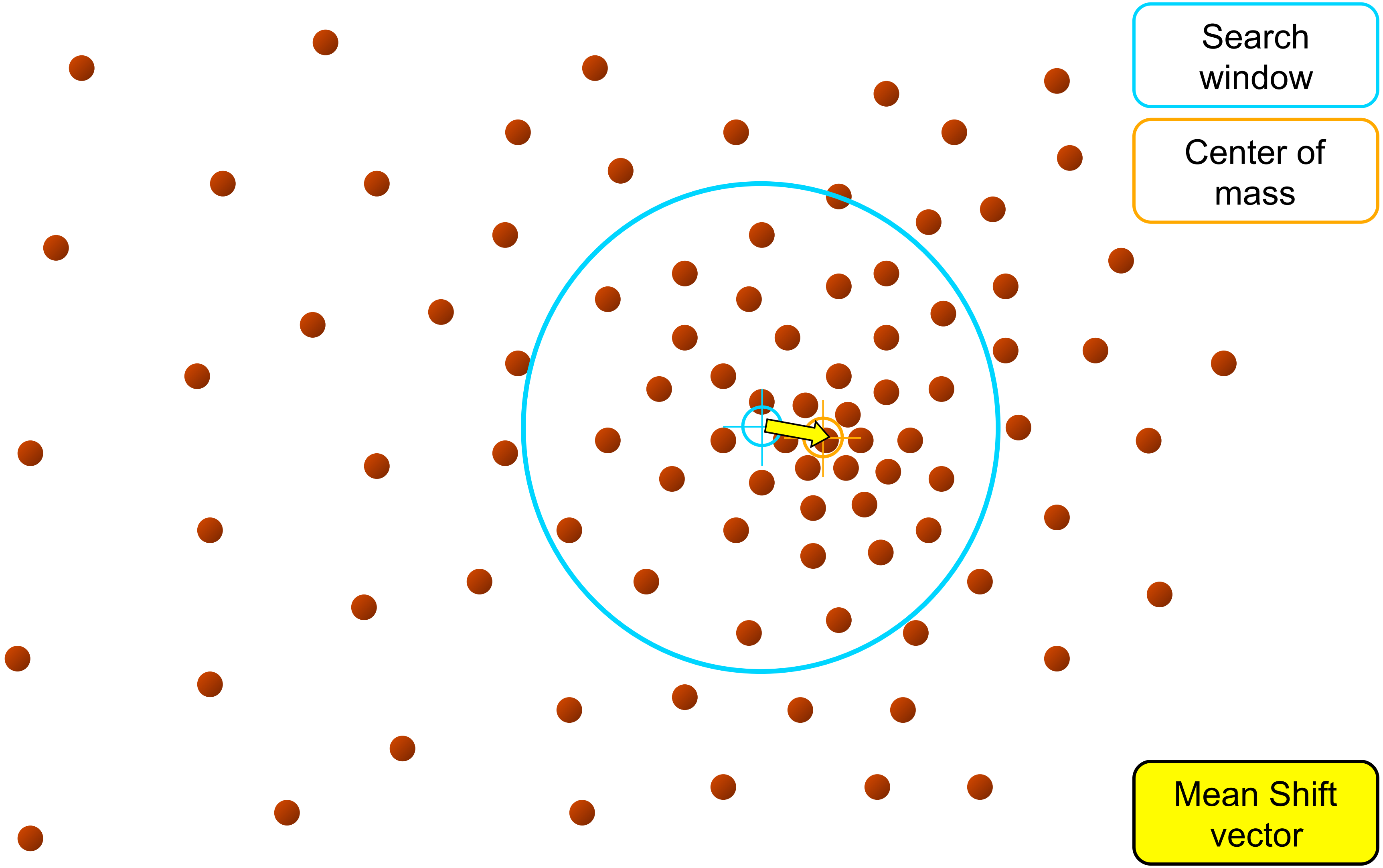
Slide by Y. Ukrainitz & B. Sarel

Mean shift



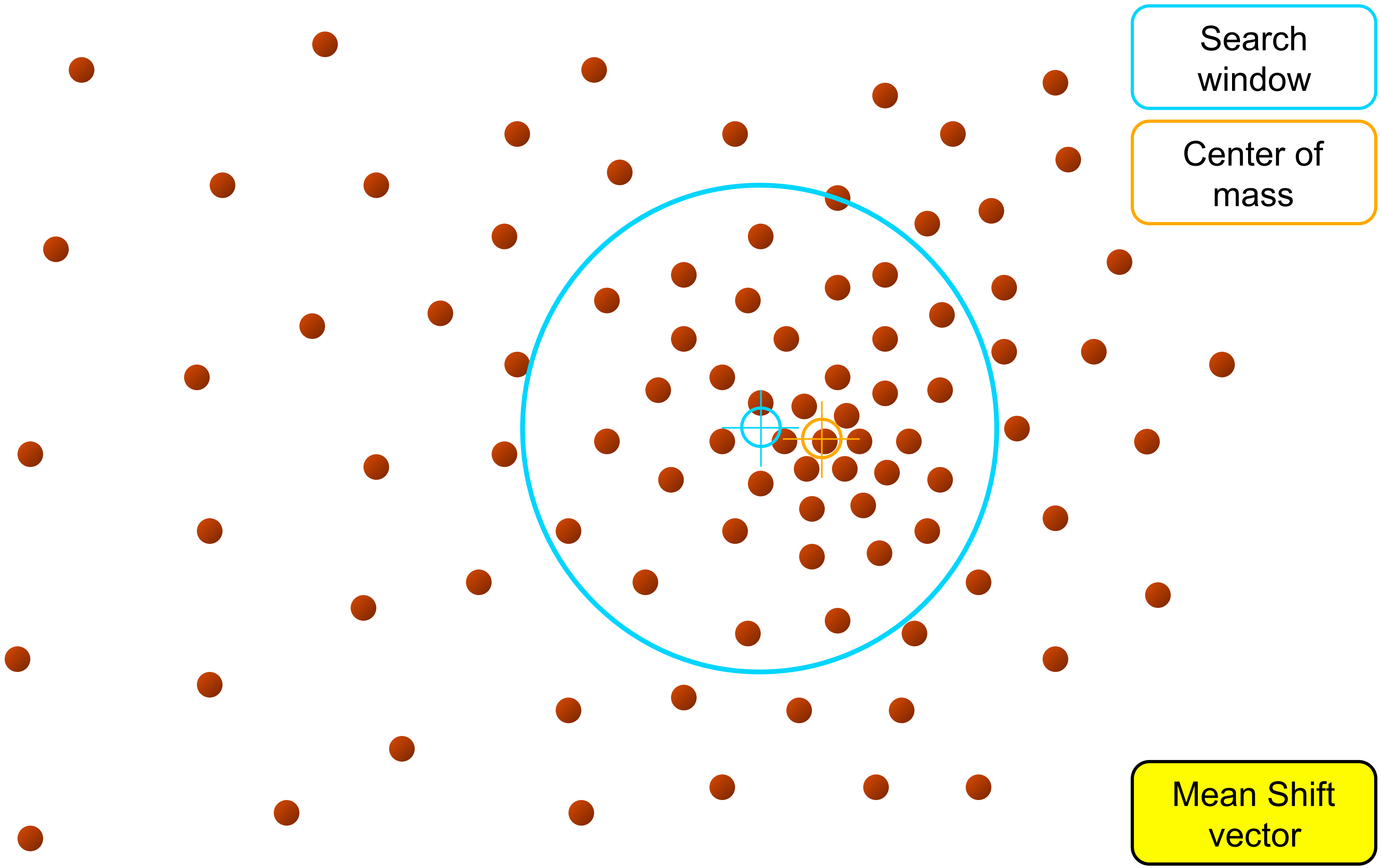
Slide by Y. Ukrainitz & B. Sarel

Mean shift



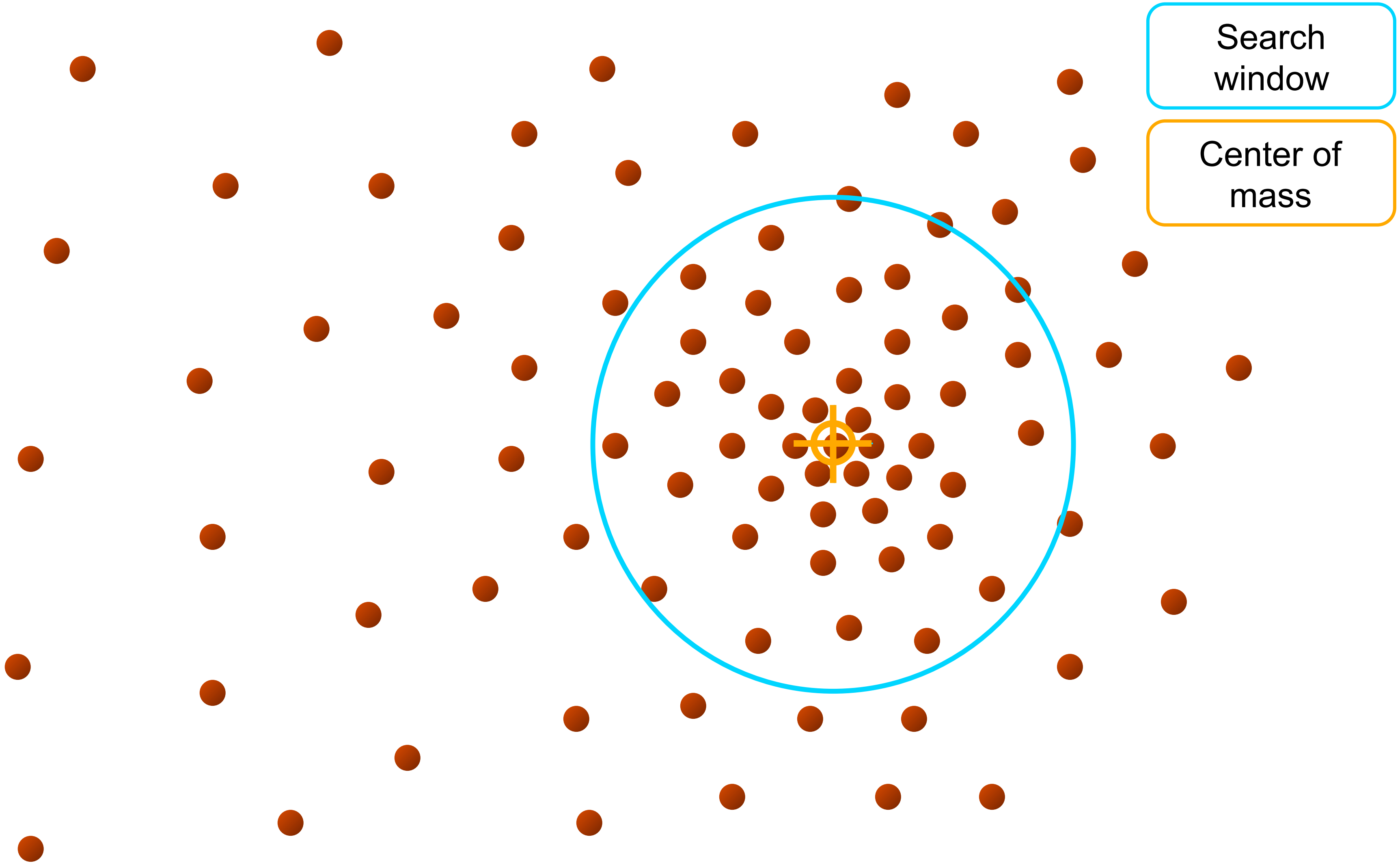
Slide by Y. Ukrainitz & B. Sarel

Mean shift



Slide by Y. Ukrainitz & B. Sarel

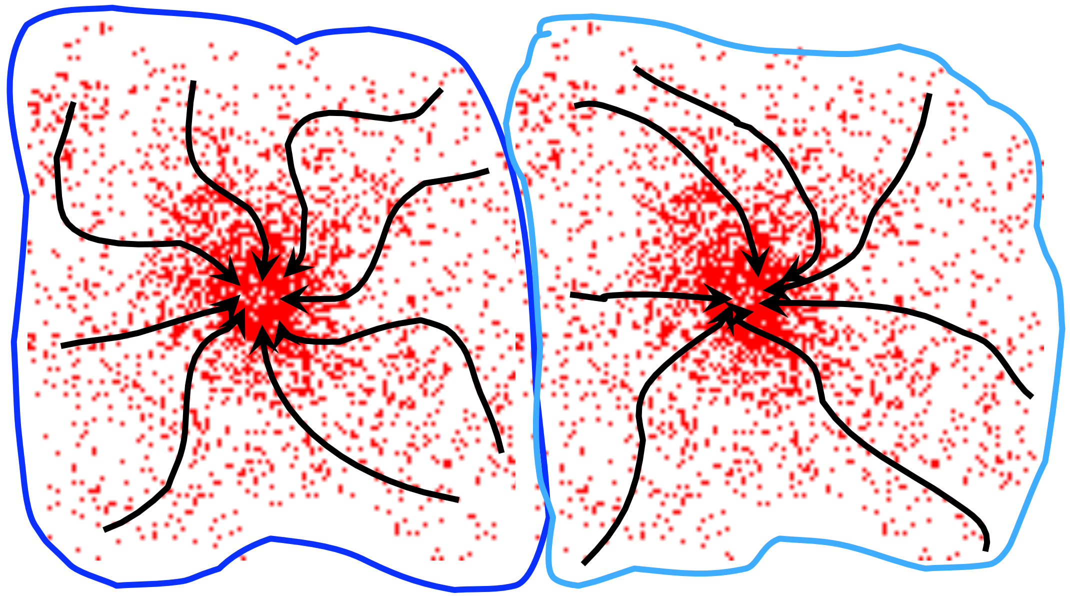
Mean shift



Slide by Y. Ukrainitz & B. Sarel

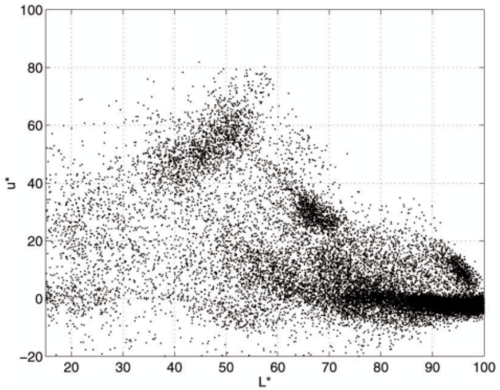
Mean shift clustering

- Cluster: all data points in the attraction basin of a mode
- Attraction basin: the region for which all trajectories lead to the same mode

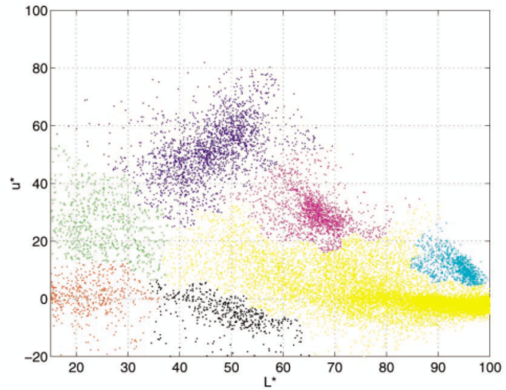


Mean shift clustering/segmentation

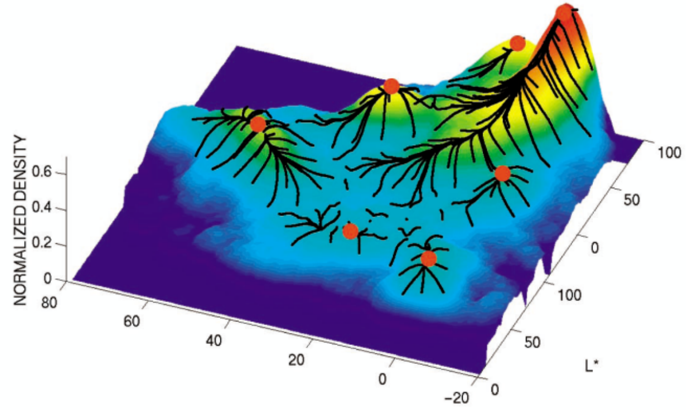
- Find features (color, gradients, texture, etc)
- Initialize windows at individual feature points
- Perform mean shift for each window until convergence
- Merge windows that end up near the same “peak” or mode



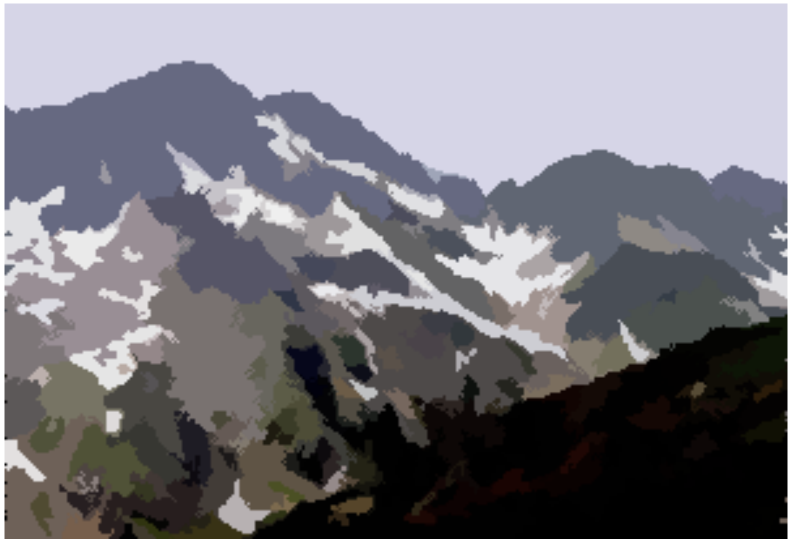
(a)



(b)



Mean shift segmentation results



http://www.caip.rutgers.edu/~comanici/MSPAMI/msPamiResults.html

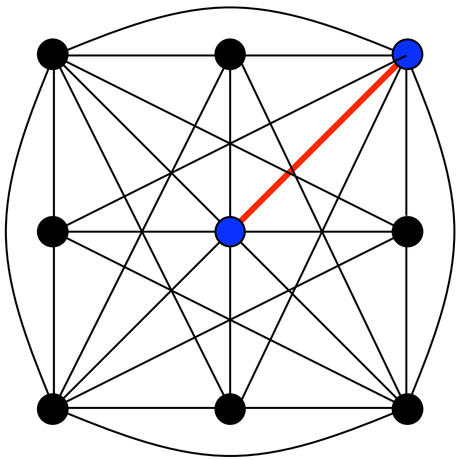
More results

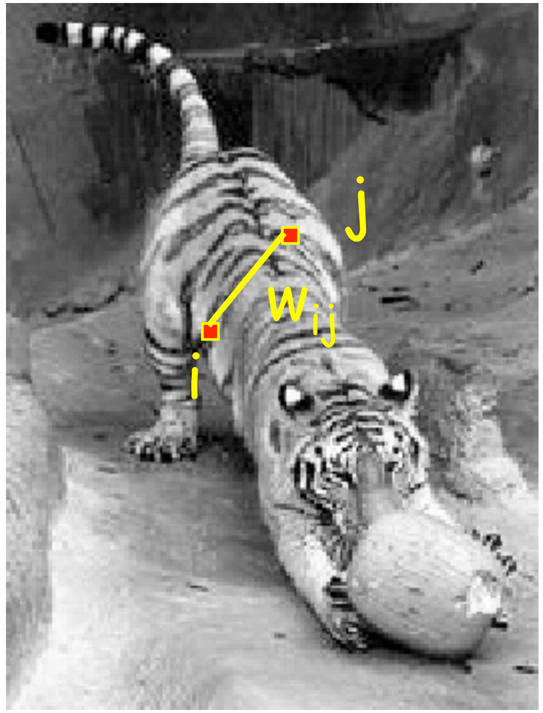
More results

Mean shift pros and cons

- Pros
  - Does not assume spherical clusters
  - Just a single parameter (window size)
  - Finds variable number of modes
  - Robust to outliers
- Cons
  - Output depends on window size
  - Computationally expensive
  - Does not scale well with dimension of feature space

Images as graphs

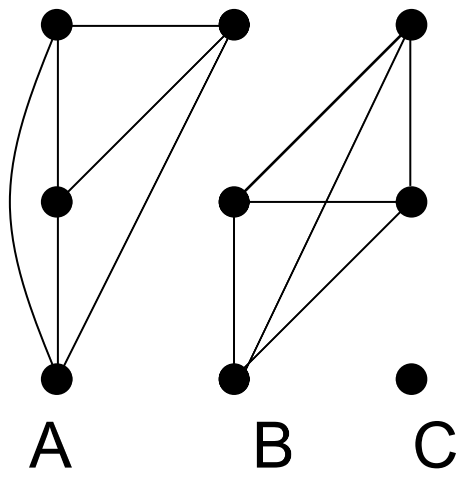




- Node for every pixel
- Edge between every pair of pixels (or every pair of "sufficiently close" pixels)
- Each edge is weighted by the *affinity* or similarity of the two nodes

Source: S. Seitz

Segmentation by graph partitioning



- Break Graph into Segments
  - Delete links that cross between segments
  - Easiest to break links that have low affinity
    - similar pixels should be in the same segments
    - dissimilar pixels should be in different segments

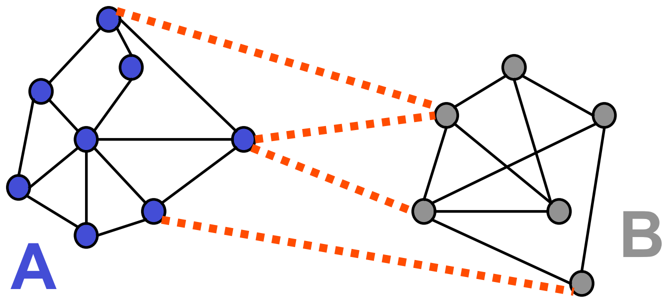
Source: S. Seitz

Measuring affinity

- Suppose we represent each pixel by a feature vector **x**, and define a distance function appropriate for this feature representation
- Then we can convert the distance between two feature vectors into an affinity with the help of a generalized Gaussian kernel:

$$\exp\left(-\frac{1}{2\sigma^2}\operatorname{dist}(\mathbf{x}_i,\mathbf{x}_j)^2\right)$$

Graph cut



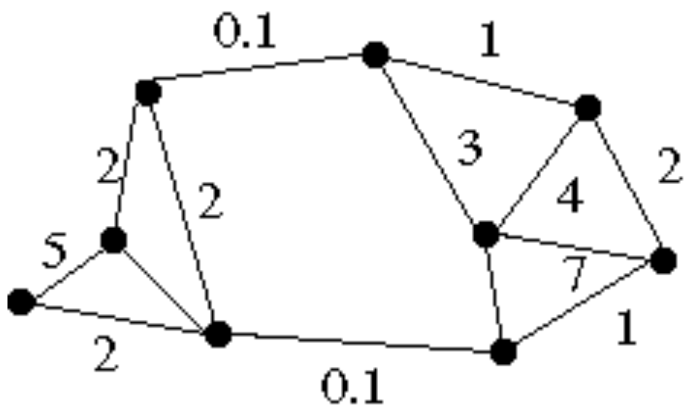
- Set of edges whose removal makes a graph disconnected
- Cost of a cut: sum of weights of cut edges
- A graph cut gives us a segmentation
  - What is a "good" graph cut and how do we find one?

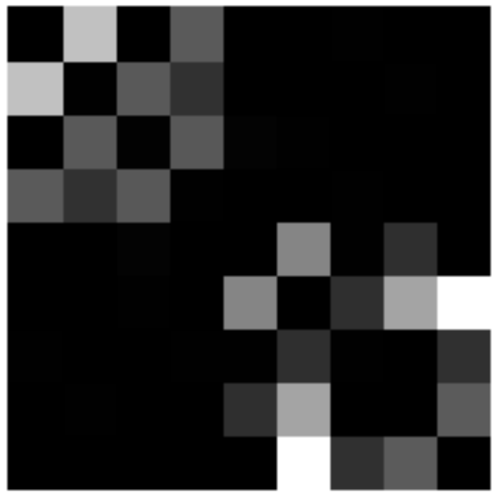
Source: S. Seitz

Minimum cut

- We can do segmentation by finding the *minimum cut* in a graph
  - Efficient algorithms exist for doing this

Minimum cut example

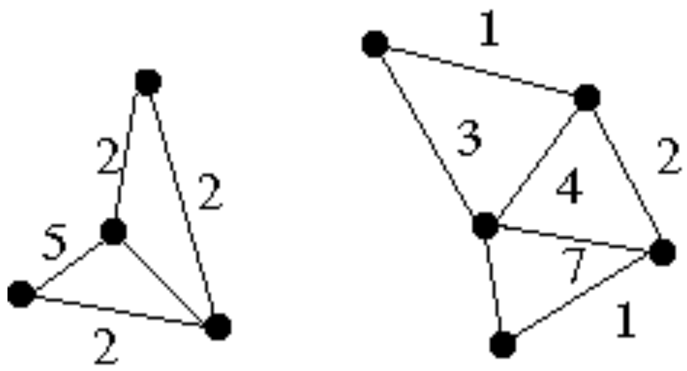


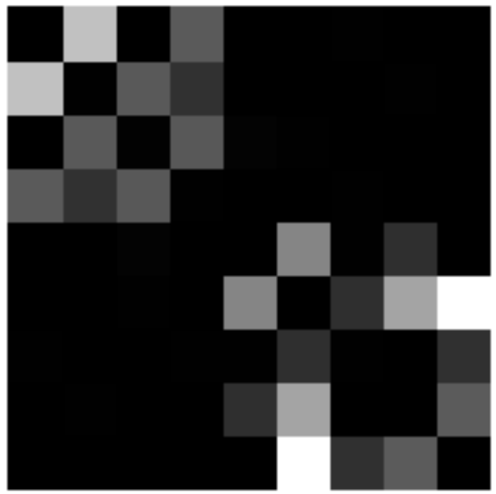


Minimum cut

- We can do segmentation by finding the *minimum cut* in a graph
  - Efficient algorithms exist for doing this

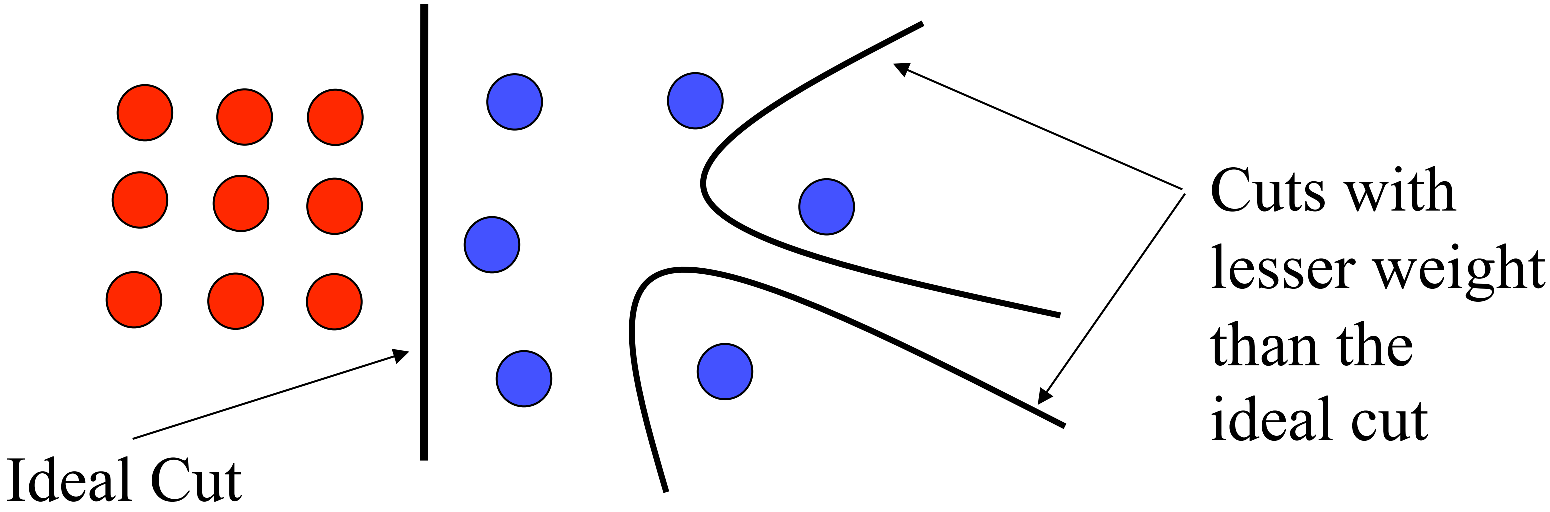
Minimum cut example





Normalized cut

- Drawback: minimum cut tends to cut off very small, isolated components



* Slide from Khurram Hassan-Shafique CAP5415 Computer Vision 2003

Normalized cut

- Drawback: minimum cut tends to cut off very small, isolated components
- This can be fixed by normalizing the cut by the weight of all the edges incident to the segment
- The *normalized cut* cost is:

$$\frac{w(A,B)}{w(A,V)} + \frac{w(A,B)}{w(B,V)}$$

w(*A*, *B*) = sum of weights of all edges between *A* and *B*
w(A,V) = sum of weights of all edges between A and all nodes

J. Shi and J. Malik. [Normalized cuts and image segmentation.] PAMI 2000

Normalized cut

- Let W be the adjacency matrix of the graph
- Let D be the diagonal matrix with diagonal entries $D(i, i) = \Sigma_j W(i, j)$
- Then the normalized cut cost can be written as

$$\frac{y^T (D - W) y}{y^T D y}$$

where y is an indicator vector whose value should be 1 in the ith position if the ith feature point belongs to A and a negative constant otherwise

J. Shi and J. Malik. Normalized cuts and image segmentation. PAMI 2000

Normalized cut

- Finding the exact minimum of the normalized cut cost is NP-complete, but if we *relax* y to take on real values, then we can minimize the relaxed cost by solving the *generalized eigenvalue problem* $(D - W)y = \lambda Dy$
- The solution y is given by the generalized eigenvector corresponding to the second smallest eigenvalue
- Intutitively, the ith entry of y can be viewed as a "soft" indication of the component membership of the ith feature
    - Can use 0 or median value of the entries as the splitting point (threshold), or find threshold that minimizes the Ncut cost

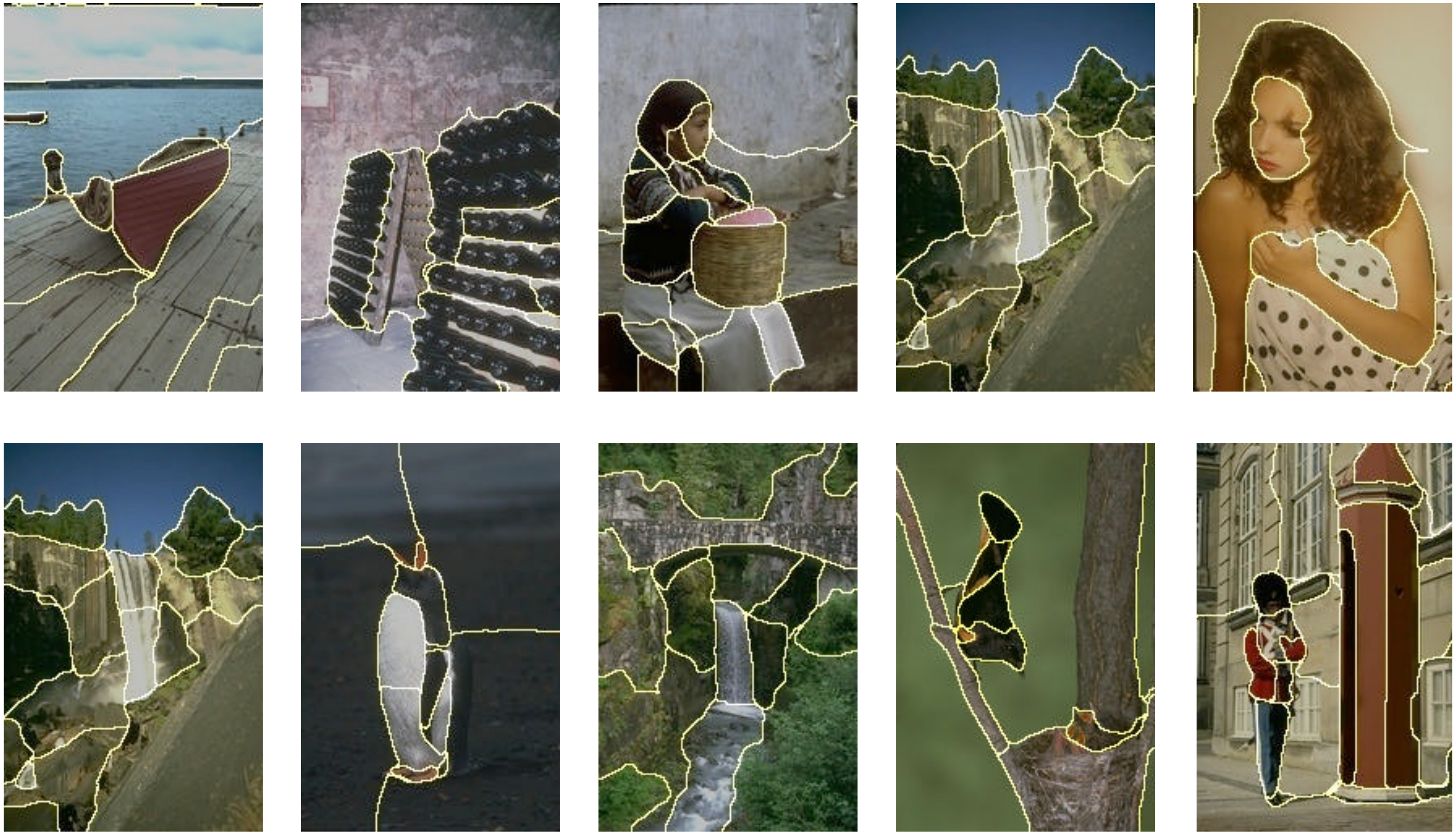
Normalized cut algorithm

1. Represent the image as a weighted graph $G = (V,E)$, compute the weight of each edge, and summarize the information in D and W
2. Solve $(D - W)y = \lambda Dy$ for the eigenvector with the second smallest eigenvalue
3. Use the entries of the eigenvector to bipartition the graph

To find more than two clusters:

- Recursively bipartition the graph
- Run k-means clustering on values of several eigenvectors

Experimental Results

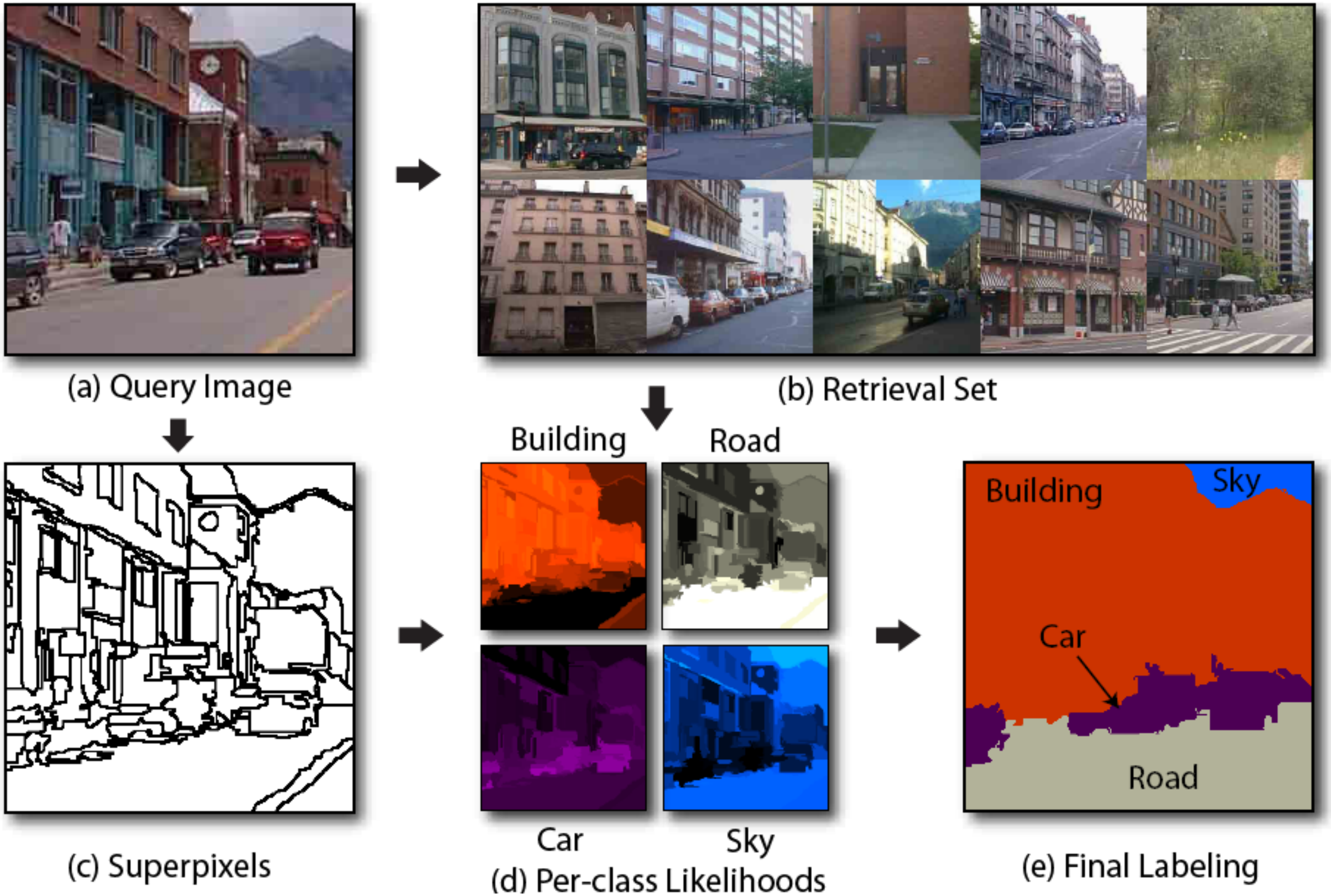


http://www.cs.berkeley.edu/~fowlkes/BSE/

Normalized cuts: Pro and con

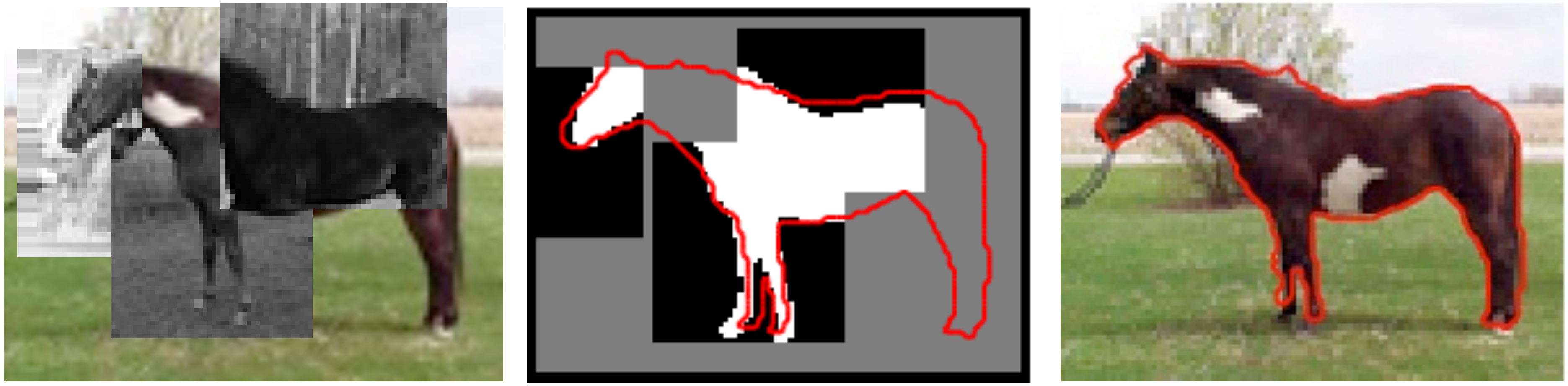
- Pros
  - Generic framework, can be used with many different features and affinity formulations
- Cons
  - High storage requirement and time complexity
  - Bias towards partitioning into equal segments

Segments as primitives for recognition



J. Tighe and S. Lazebnik, ECCV 2010

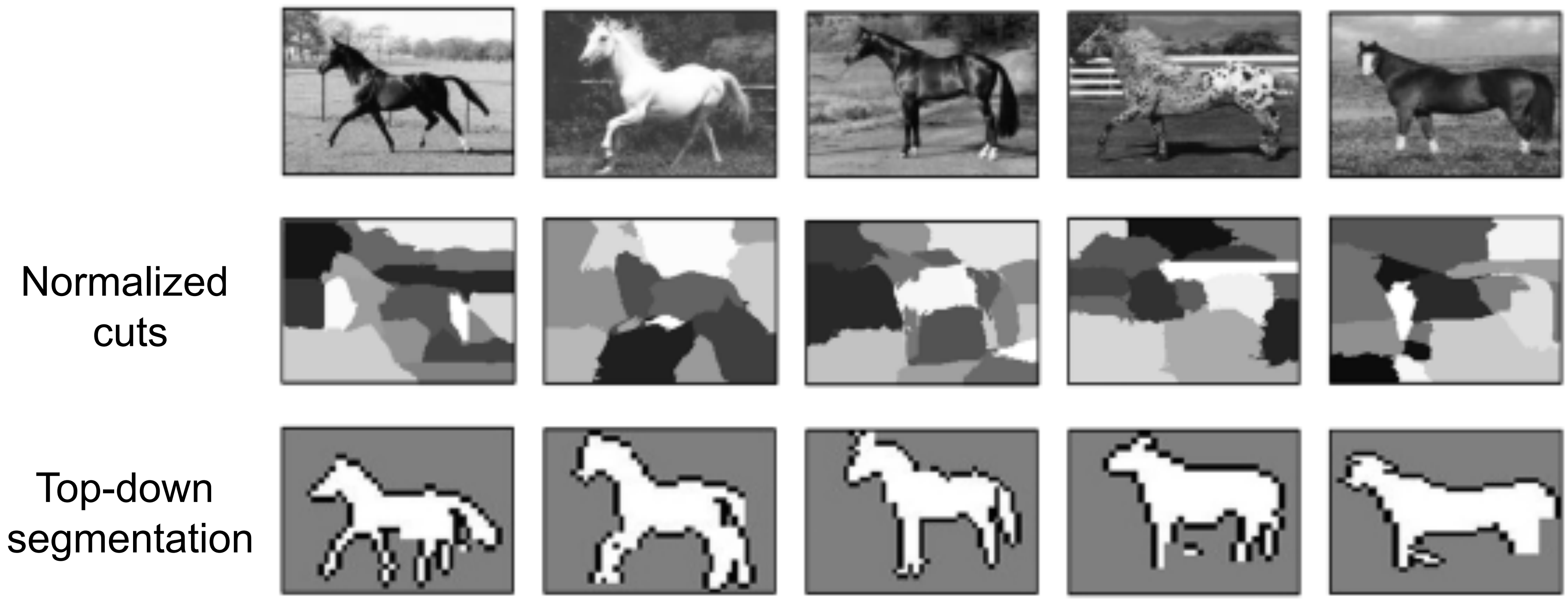
Top-down segmentation



E. Borenstein and S. Ullman,
"Class-specific, top-down segmentation," ECCV 2002

A. Levin and Y. Weiss,
"Learning to Combine Bottom-Up and Top-Down Segmentation," ECCV 2006.

Top-down segmentation

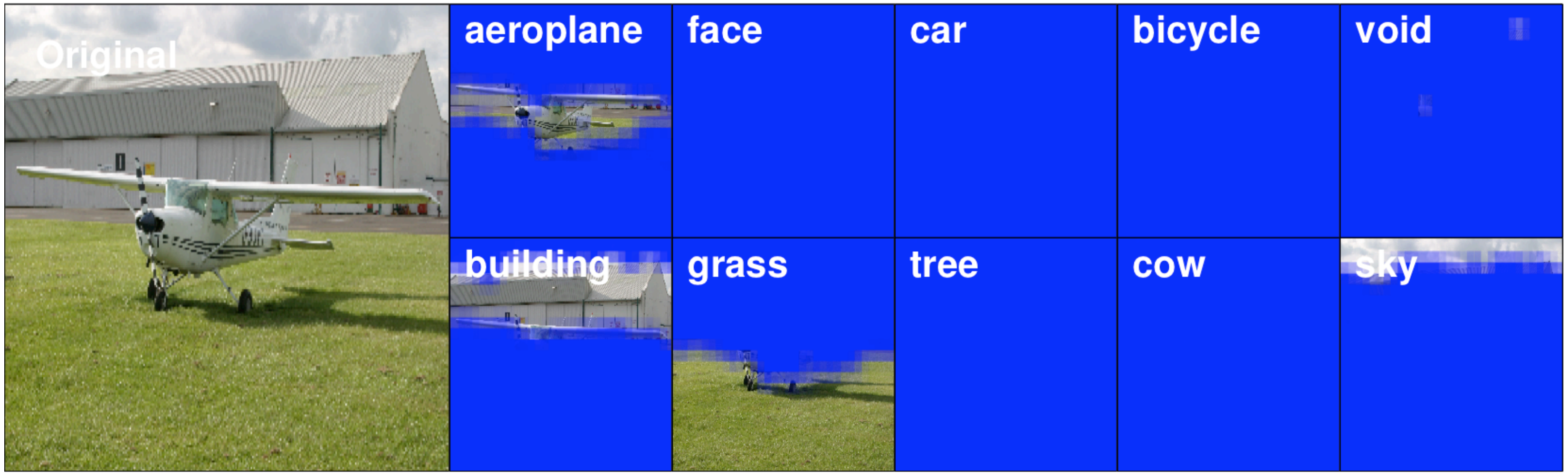


E. Borenstein and S. Ullman, "Class-specific, top-down segmentation," ECCV 2002

A. Levin and Y. Weiss, "Learning to Combine Bottom-Up and Top-Down Segmentation," ECCV 2006.

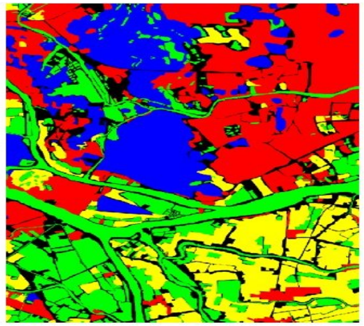
Markov random fields for pixel labeling

- Labeling each pixel with a category
- Markov random field takes into account spatial consistency



Learning MRF models of image regions

- All pixels labeled in train images

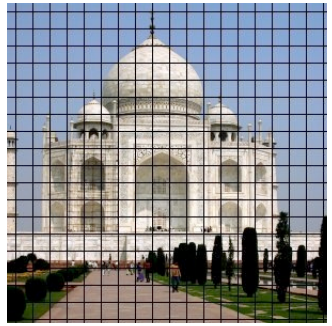


- Model appearance of individual pixels for categories P(X|Y)
  - Features: Color, texture, relative position in image model
- Model distribution of region labels P(Y)
  - Spatially coherency: neighboring regions tend to have the same label
- Inference problem: Given image X, predict region labels Y
  - use the models p(Y) and p(X|Y) to define p(Y|X)

Modeling spatial coherency

Markov Random Fields for image region labeling

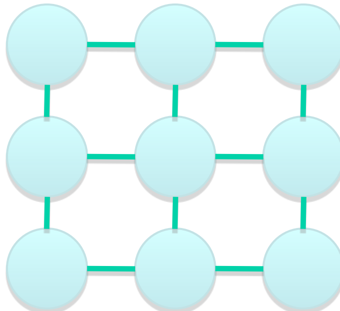
- Divide image in rectangular regions (~1000 per image)
- Each region variable y_i can take value 1, …, C for categories



MRF defines probability distribution over region labels

- Variables independent of others given the neighboring variables
- 4 or 8 neighborhood system over regions

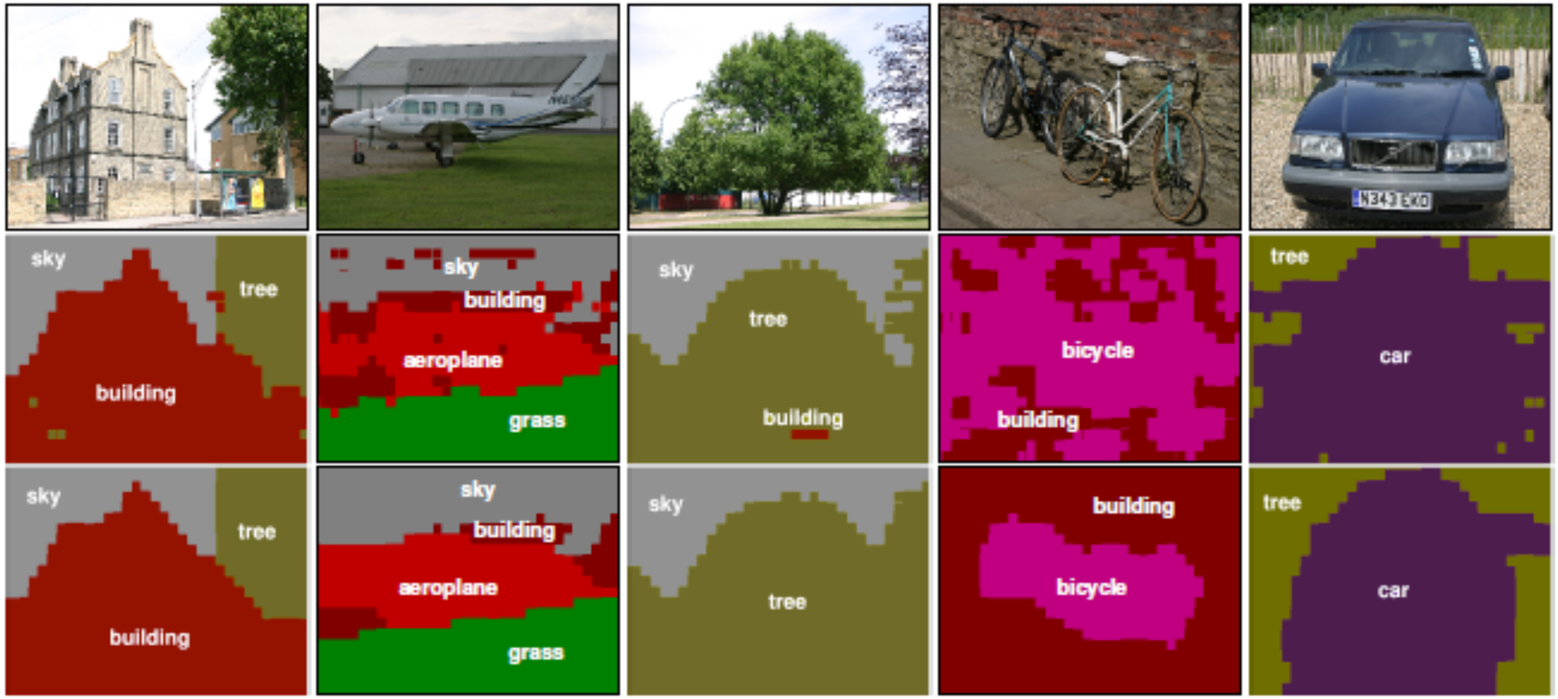
$$p(Y) = \frac{1}{Z}\exp(-E(Y)), \qquad E(Y) = \sum_i \sum_{j \in N(i)} E(y_i, y_j)$$



Potts model common choice for pair-wise interactions:

$$E(y_i, y_j) = \begin{cases} -\sigma & \text{if } y_i = y_j \\ 0 & \text{otherwise} \end{cases}$$

Example results



Middle row: pixel-wise labeling; bottom row: Pixels + MRF